Summer 8-2023

Attention and Task Engagement During Automated Driving

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ATTENTION AND TASK ENGAGEMENT DURING AUTOMATED DRIVING

by

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B.S. May 2017, Old Dominion University
M.S. December 2019, Old Dominion University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

PSYCHOLOGY

OLD DOMINION UNIVERSITY
August 2023

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ABSTRACT

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James Richard Unverricht
Old Dominion University, 2023
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Many young drivers suffer fatal crashes each year in the United States at a rate approximately three times greater than more experienced drivers. Automated driving systems may serve to mitigate young drivers high crash rates but remain underexplored in research. This dissertation project examined the effects of levels of automation and interestingness of auditory clips on latent hazard anticipation in young drivers during simulated driving. Participants drove a vehicle at varying levels of vehicle automation (SAE Level 0, 2, or 3) in simulated scenarios, each containing a latent hazard event during which a boring, neutral, or interesting auditory clip was played. After completing all scenarios, participants completed an auditory stimuli recognition test and a questionnaire measuring the drivers' calibration of their LHA performance. Results demonstrated that those in the L3 condition anticipated significantly fewer hazards than those in the L0 condition, corroborating previous research (Samuels et al., 2020). However, those in the L3 condition were also significantly poorer at anticipating latent hazards than those in the L2 condition, suggesting the importance of instruction on a drivers' attentional allocation policy. A tradeoff was found between latent hazard anticipation and auditory recognition scores indicating the allocation of limited attentional resources as predicted by the Yamani and Horrey (2018) model. Interestingness of auditory stimuli had little to no effect on latent hazard anticipation. In general, automation may improve the multitasking ability of a young driver piloting L2 automation, but this benefit is lost for drivers of L3 automation. Instead,

young drivers piloting L3 automation may anticipate latent hazards at rates as low as those observed in newly licensed drivers, and may be completely unaware of their failure to anticipate such hazards. The current research illustrates the criticality of user guidance when handling automated driving systems and serves as one step towards understanding the complex relationship between human drivers and automated systems.

To Nini, whose unwavering devotion and radiant spirit has illuminated my path, transforming this dissertation journey into a tapestry of cherished memories and boundless inspiration, forever grateful for having you as my muse

ACKNOWLEDGEMENTS

I would like to acknowledge the countless number of people who have helped me along my journey, from those who met me as a driven yet naive student at a local community college to my friends, colleagues, and mentors I have cultivated in my professional life. First and foremost, I would like to thank Dr. Yusuke Yamani for his guidance and friendship. From conversations over midday coffee to laughing over shared academic experiences, the memories I take from these last six years I will cherish for the rest of my life. Thank you for not only helping me become a better researcher, but for encouraging me to think bigger and shoot for the stars.

Second, I would like to thank my ODU family, both past and present, who have advised, mentored, and developed who I am today. Specifically, I would like to thank my committee members Dr. Xiao Yang and Dr. Kun Xie who have given me invaluable advice towards my dissertation work. Thank you for serving on my committee. I would also like to thank Peggy Kinard, Dr. Jing Chen, Dr. Bill Horrey, Linda Forchas, Dr. James Bliss, Dr. Jeremiah Still, Dr. Barbara Winstead, Dr. Violet Xu, Dr. Ryan McGarry, Dr. Chris Arra, Dr. Eric Chancey, Bill Buck, soon to be doctors Mishler, Yahoodik, Long, and Sato, and the late Mary Boswell. How each of you helped or motivated me would require a dissertation to describe, words cannot express my gratitude towards you and the myriad of others who helped me along this journey.

Finally, thank you to my family and friends that have supported me across these many years. Specifically, thank you to my brother Kwaku and my Grandmother Carmen, for the last thirteen years you both believed that I would make this dream a reality, even when I did not. My wonderful parents, both old and new, nephews, siblings, and all other family and friends, thank

you, this accomplishment is a mosaic of all the love you have given me. It would not exist without you. This is not the end, but the beginning of a new and beautiful journey.

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CHAPTER I

INTRODUCTION

Recent technological development has made automation technology ubiquitous in everyday tasks and allowed for the design and operation of human-machine systems in a myriad of professional domains such as agriculture (Jha et al., 2019), airport security (Korbelak et al., 2018), and firefighting (Pritzl et al., 2021). One such domain is surface transportation where a range of vehicle automation has been conceptualized (SAE, 2021) with some automated features being commercialized in developed countries such as the U.S., Germany, and Australia. (Cicchino, 2016; Lee & Hess, 2020). Automated driving system (ADS) refers to a set of automated technologies that partially or fully replace drivers' vehicle control abilities including longitudinal and lateral control of the vehicle with or without human intervention depending on levels of automation (SAE, 2021). Despite its popularity and prospect of fundamentally changing road transportation in the future (Yang & Fisher, 2021), the psychological mechanisms that regulate intricate interactions between a human driver and ADS are yet unknown and under-explored in the literature.

Previous researchers proposed that human operators possess a limited pool of attentional resources that can be mobilized to different human information processors to support their task performance (Kahneman, 1973; Norman & Bobrow, 1975). In the context of automated driving, Yamani and Horrey (2018) expanded the unitary capacity theory (Kahneman, 1973) to integrate levels of automation, proposing that automation frees attentional resources for the amount corresponding to the level of automation, which can be reallocated to support other concurrent tasks. Thus, the model predicts that drivers could allocate more of their attention towards the driving task when supported by a greater level of automation. To test this hypothesis, Samuel and colleagues (2020) asked drivers to navigate a series of safety-critical scenarios in a driving simulator and found that the participants failed to glance at a critical visual area that can contain an unmaterialized, or latent, hazard more frequently when they drove the vehicle with higher levels of automation. The results were unexpected and underscore necessity for further experimentation. For example, it is possible that drivers with higher levels of ADS allocated their attention to a driving-unrelated task such as mind-wandering and neglected to attend to the forward roadway.

As Samuel and colleagues (2020) studied, latent hazard anticipation (LHA) represents a driver's ability to detect a latent hazard that exists in a driving scene and has not yet materialized. Successful LHA requires all three levels of situation awareness that are resource-dependent (e.g., Yamani et al., 2021; Endsley, 1995). That is, drivers must *perceive* surrounding vehicles and road geometry in their immediate road environment, *comprehend* what the perceived items mean, and *project* how the road environment evolves over time. For example, a driver could perceive the presence of a crosswalk and a van parked near the crosswalk, comprehend that the crosswalk means a pedestrian may pass there, and anticipate that a pedestrian may appear from behind the parked van as they approach the crosswalk. The literature indicates that LHA performance tends to be poor in young drivers with limited driving experiences (Unverricht et al., 2018a), suggesting that LHA tasks are resource-limited (Yamani et al., 2021).

The purpose of this dissertation is to examine how different levels of automation affects a drivers' LHA performance in a driving simulator. To explore how spare resources are mobilized during automated driving, we will ask drivers to listen to an auditory clip with its interestingness manipulated mirroring Horrey and colleagues' (2017) study while they are driving through a simulated scenario containing a latent hazard. Additionally, as an exploratory purpose, I will measure driver calibration to explore if any discrepancy between drivers' subjective and objective performance scores exists as a function of LOA (Horrey et al., 2015; Roberts et al., 2016; Unverricht et al., 2020).

CHAPTER II

LITERATURE REVIEW

Young Drivers

Although fatal crash rates among passenger vehicle drivers have been decreasing partially due to better vehicle safety technology and changes in driver attitudes (National Safety Council, 2020), the number of deaths per year and costs of those deaths are staggering. For example, in 2019, over 36,000 people died in motor vehicle crashes costing a total of $242 billion dollars (IIHS, 2021). Young drivers aged 16 – 19 are over-represented in fatal crashes, suffering crash rates three times greater than that of drivers aged 20 and older (IIHS, 2021). Immaturity and risk-taking are two factors theorized to be responsible for young drivers' high crash rates (Curry et al., 2015). However, McKnight & McKnight (2003) demonstrated cognitive factors such as poor search behavior and insufficient attention as stronger predictors of young drivers' crash rates rather than risk-taking behaviors or immaturity. Specifically, out of 2,128 police reports of non-fatal crashes including young drivers, 23% were attributed to deficiencies in attention, 43.6% were attributed to deficiencies in drivers' visual search behaviors, and 20.8% were attributed to deficiencies in speed adjustment relative to the environment. One implication from this finding is that young drivers are not helpless until they mature but that they can potentially decrease their crash rates through improving specific perceptual-cognitive skills.

Latent Hazard Anticipation

One perceptual-cognitive skill that is critical for young drivers' safety is hazard anticipation (Pradhan et al., 2005; Fisher et al., 2006; McKenna et al., 2006; Unverricht et al., 2018; Yamani et al., 2016). Hazard anticipation requires the driver to perceive, comprehend, and anticipate hazards on the roadway. Recent work suggests that even untrained college students are poor at anticipating hazards (Krishnan et al., 2019; Yahoodik & Yamani, 2021), showing that the lack of latent hazard anticipation skills is a pervasive issue among young drivers. Latent hazards are imminent hazards that have not yet materialized on the roadway (Unverricht et al., 2018). For example, imagine a driver arriving at a T-intersection moderated by a stop sign with heavy foliage blocking the left-hand side. From this position, the foliage prevents the driver from viewing any potential vehicles that may materialize as they perform a right-hand turn. In this example, it is the drivers' anticipation of a potential vehicle traveling behind the foliage that represents their ability to successfully anticipate a latent hazard.

Latent hazard anticipation is often measured by tracking a drivers' eye glances during a latent hazard event. Each latent hazard scenario contains the pre-determined target zone containing a latent hazard and the launch zone representing a spatial area within which the driver must glance toward the target zone. A driver's glance is classified as a success if the driver in the launch zone glances toward the target zone and a failure otherwise (Pradhan et al., 2005; Figure 1).

Figure 1

Latent hazard anticipation example.

Note. The blue square represents the launch zone where the driver would need to visually observe the red circle or target zone to avoid a potential hazard (Unverricht et al., 2018a).

Novice drivers have demonstrated poorer latent hazard anticipation performance than more experienced drivers (Garay-Vega et al., 2007; Pradhan et al., 2005). For example, in a seminal study (Pradhan et al., 2005), participants were placed into a driving simulator and exposed to 16 different LHA events. Their results showed that novice drivers anticipated latent hazards in around half as many events as expert drivers. In another experiment, researchers tested novice, experienced, and commercial drivers' ability to anticipate latent hazards. They found novice drivers were the poorest at anticipating latent hazards (Crundall et al., 2012). Additionally, taxi drivers were better than all other groups at anticipating hazards, a finding indicating that LHA improves with experience and knowledge rather than a decrease in risky driving behaviors caused by age.

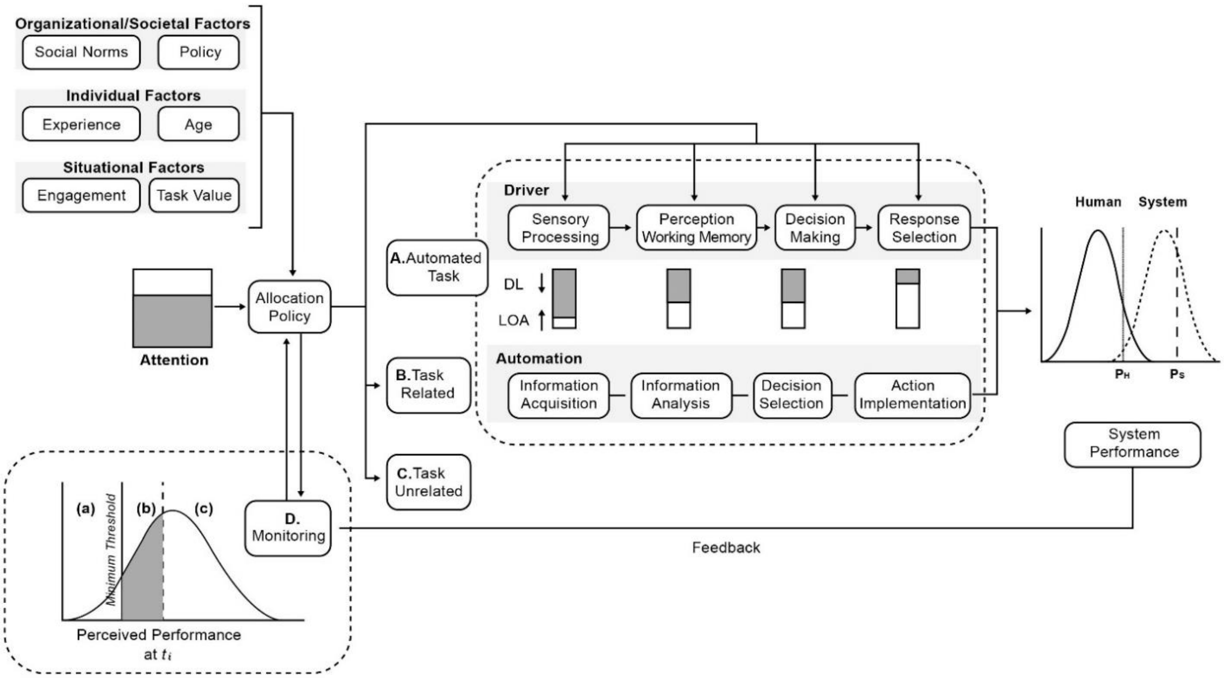
From a practical perspective, studying LHA has the potential to mitigate young driver's crash rates through training and design. For example, researchers developed the Risk Awareness and Perception Training (RAPT) program that has shown to improve young drivers' ability to anticipate hazards (Pollatsek et al., 2006; Pradhan et al., 2006a; 2009; Yahoodik & Yamani, 2021; for a review of several hazard anticipation training programs see Unverricht et al., 2018a). RAPT's effect on LHA performance has been validated both in a driving simulator and in the field (Pradhan et al., 2006b; Taylor et al., 2011). Additionally, trained participants have shown retention of their improved LHA performance up to eight months (Taylor et al., 2011). Additionally, a large-scale on-road evaluation study showed that male teen drivers who received RAPT training not only showed an improvement to their LHA skills, but also showed a 24% decrease in crash rates over 12 months post-training compared to non-trained drivers (Thomas et al., 2016). Although the effect of training on LHA is well developed and documented, how design solutions such as automated driving systems and LHA interact remain relatively unexplored.

How the implementation of ADS may affect LHA can be described using two theoretical models, Wicken's human-information processing (HIP; Wickens, 2002) and Yamani and Horrey's (2018) model of human-automation interaction. The HIP model posits a series of information processing stages such as perception, comprehension, decision-making, response selection, and response execution, each requiring attentional resources. Attentional resources are a psychological construct that supports information-processing stages of a human conceptualized as a limited-capacity information processor (Gopher & Donchin, 1986; Kahneman, 1973; Moray, 1967; Wickens, 2002). Attentional resources can be considered analogous to a fuel that information processing requires. However, the amount of attention that an individual has is theorized to be limited (Moray, 1967), requiring the individual to selectively allocate attention to tasks, a process itself that is thought to require attentional resources (Norman & Shallice, 1986;

Schumacher et al., 2001). For drivers performing latent hazard anticipation, each individual stage of anticipation (e.g., perception, comprehension, and projection) requires sufficient attentional resources to be able to ultimately produce road awareness and safe driving behaviors. Yamani and Horrey's (2018) model of human-automation interaction provide a taxonomy for understanding how different levels of automation could impact a driver's attention allocation in the driving environment (Figure 2). The model states that as the level of automation increases at a stage of information processing, a corresponding amount of attentional resources of the driver is freed and reduces workload. Then, the combined performance of both the human and machine feed into the system performance, monitored by the human via feedback. Both the monitoring of performance and factors such as experience and task engagement influence the attentional allocation strategy of the driver. The model describes how a driver can allocate their attention across different processing stages or tasks, be they automated tasks, driving related tasks, or driving unrelated tasks. The Yamani and Horrey (2018) model predicts three potential outcomes of using automation with driving: the driver can allocate the additional resources to monitoring the automation, the driver can allocate the additional attentional resources to driving critical tasks such as HA, or the driver could allocate those attentional resources towards non-driving related tasks. For young drivers, automation provides the potential to improve their LHA if they effectively allocate the freed attentional resources towards that driving-related task.

Figure 2

Yamani and Horrey's (2018) model of human-automation interaction.



Automated Vehicles and Automation

Automated vehicles refer to vehicles equipped with technologies that support from SAE levels 1-4 while autonomous vehicles refer to those at SAE level 5 (SAE, 2021). Lower levels of automation (L1 and L2) automate specific functions of the driving task such as speed or lateral control and require the driver to supervise and take over the automation when needed. Higher levels of automation, such as L3, allow the drivers to disengage from the driving task, only responsible for acting when prompted by the vehicle. The highest levels of automation, such as L4, and the autonomous level of L5, do not require a driver to take over control of the vehicle and is analogous to a "driver-less taxi" (SAE, 2021).

Automation refers to when a machine either completely or partially subsumes a function or role that was previously performed by a human (Bainbridge, 1983). For AV's, this means the automation can be responsible for executing driving tasks such as detecting potential forward collisions, maintaining speed, and keeping the vehicle in the center of the lane. Parasuraman and colleagues (2000) mapped automation across the human-information processing spectrum (e.g. HIP model), information acquisition, information analysis, decision-making, and response execution. In addition, the authors presented levels of automation (LOA) to describe how a vehicle could be variably automated across the information-processing stages but also within each stage. For example, automation can be high at the perception stage but low at the response execution stage. In relation to ADS, by activating cruise control (CC), the driver no longer needs to press the break or acceleration pedal to maintain their current speed. But, if the need to decelerate or accelerate were to arise, the driver would need to take control. Autopilot, on the other hand, partially takes the responsibility for perception, analysis, decision-making, and response execution, with the condition that the driver supersede the machine if it were to fail. CC represents a L1 automated driving system and Tesla's Autopilot represents a L2 automated driving system (SAE, 2021). For both systems, the driver remains responsible for the safety of the vehicle, but the automation serves as support systems to improve the drivers' performance. In this context, automation can improve performance through reducing drivers' workload (Parasuraman & Riley, 1997; De Winter et al., 2014), freeing attentional resources for situation awareness (Parasuraman et al., 2000; De Winter et al., 2014) and potentially LHA (Yamani et al., 2018). However, one strong take-away from Parasuraman and colleagues (2000) is that applying automation to a system does not simply supplant human behavior but holds the potential to change that behavior.

High levels of automation may turn the driver from an experienced operator into an inexperienced monitor of automation (Casner et al., 2016; Hancock et al., 2020; Parasuraman et al., 2000), of which humans have shown to be poor at supervising (Parasuraman & Riley, 1997). Changing a driver from an active participant to an inactive supervisor may lead to cognitive underload (Young & Stanton, 2002) or passive fatigue (Saxby et al., 2013) causing drivers to engage in non-driving related tasks (NDRTs) to circumvent (Carsten et al., 2012). In addition, higher levels of automation in motor vehicles can lead to degradation in drivers' situation awareness and cause the driver to become "out of the loop" (OOTL; Cunningham et al., 2015). The OOTL problem occurs when automation causes a driver to be removed from one or two primary loops (Louw et al., 2015). The first is the physical control loop, where a driver may find difficulty physically controlling the vehicle after a take-over request. Recent work has implicated that a drivers' ability to safely take-over control of a vehicle when prompted by the automation is depreciated by factors such as unnoticed mode transitions, loss of awareness of the system state, high trust and complacency scores, and passive monitoring causing a failure to visually sample safety critical such as crosswalks at intersections (Merat et al., 2019; Seppelt & Victor, 2016). Additionally, engaging in NDRTs and having the amount of time leading a take-over request be less than 10 seconds can significantly impair a drivers' ability to safely take-over control of the vehicle (Eriksson & Stanton, 2017; Wan & Wu, 2018). The other loop that can cause a driver to be OOTL is the situation awareness loop, where a driver can be removed through either visual or cognitive resources being allocated away from the driving task and the road environment.

Latent Hazard Anticipation and Automated Vehicles

Yamani and Horrey (2018) predicts that drivers piloting a vehicle at L2 automation should be able to allocate their attention to the driving related tasks better than drivers at L0.

Drivers in the L2 condition would theoretically have a larger excess of attentional resources that can be used to support information-processing stages on the driving task. If drivers allocate these additional attentional resources towards LHA, then drivers' LHA performance should increase.

However, although high LOA should improve LHA performance, high LOA has shown to either negatively affect LHA performance or hold no affect at all (Ebadi et al., 2021; Samuel et al., 2020). For example, one study demonstrated that drivers anticipated fewer hazards as the level of automation within an AV increased from L0 – L3, with L0 – L2 showing no significant difference (Samuel et al., 2020). Another study found those in the L2 automated condition anticipated 29% fewer hazards than those in the L0 manual condition (Ebadi et al., 2021). Finally, in Hatfield and colleagues (2019), drivers were given a latent hazard anticipation training program and then had to drive through multiple virtual scenarios, in either L0 or L2 conditions. They found those in L2 made fewer fixations towards the forward roadway than those in L0. Even though drivers supported by L2 ADS should be able to anticipate more hazards, they are repeatedly found to anticipate fewer.

One explanation for drivers' poor LHA performance within an automated AV is the drivers' attention allocation strategy. As stated in Yamani and Horrey (2018), a driver may allocate their attention toward the driving task, toward a driving-related task, or toward a NDRT. In general, drivers spend less time anticipating hazards while interacting with a NDRT in both L0 (Ebadi et al., 2019; He & Donmez, 2018; 2020) and L2 automated vehicles (He et al., 2021a). Additionally, while piloting a L2 automated system and interacting with a secondary visual-manual task, both novices and experts spent significantly less time viewing anticipatory cues, indicating the allocation of their visual attention is directed towards the NDRT regardless of experience (He et al., 2021a). The negative effect engaging in NDRTs has on anticipating hazards is found even when using an auditory-verbal secondary task (Ebadi et al., 2019). This is not to say that driving performance cannot be improved if attention is allocated towards driving related tasks. For example, automation improved drivers' time to collision judgements and brake reaction time when drivers allocated their excess attentional resources towards those driving related tasks (Lodinger et al., 2019). There is even some evidence that automation can improve drivers' visual scanning of anticipatory cues if they allocate their attention towards that driving related task (He et al., 2021b). One factor that can influence a driver's attention allocation strategy is task engagement (Yamani & Horrey, 2018).

Interestingness and Task Engagement

Task engagement can be defined variably as it refers to either the subjective state of the individual or as it refers to the properties of the task. For example, Matthews and colleagues (2002) defined task engagement as "a complex of energy, motivation, and concentration", a definition inherent to the subjective state of the individual. In contrast, a more commonly used model of task engagement describes engagement as the properties of a task that can promote or hinder engagement across four different stages, point of engagement, engagement, disengagement, and reengagement (O'Brien & Toms, 2008). For example, a task which is interactive, novel, and aesthetically pleasing would be inherently more engaging than a task that is passive, familiar, and repulsive. O'Brien and Toms' model of engagement promotes that engagement is facilitated through both the properties of the object and the top-down goals and perceptions of the individual.

Engaging in NDRTs can be promoted through highly engaging secondary tasks more than boring or neutral engaging secondary tasks (Dula et al., 2011; Gibson et al., 2016; Horrey et al., 2009; 2017; Klauer et al., 2015). For example, one study performed a meta-analysis of experiments investigating the effect of secondary task engagement on crash risk and found that visual-manual tasks (e.g., texting) incurred the highest crash risk, potentially due to the increased engagement intrinsic to these tasks (Klauer et al., 2015). However, this is not to say that tasks must be visual-manual to be highly engaging or that all visual-manual tasks are engaging. Another study (Dula et al., 2011) assigned drivers to one of three conditions, no phone call, emotional phone call, or mundane phone call, all while driving in a simulated environment. Although the mundane phone call group conducted more dangerous driving behaviors than the no call group, the emotional call group engaged in significantly more dangerous driving behaviors than both the no call and mundane call (Dula et al., 2011). These results indicate that higher levels of engagement can promote worse distracted driving behaviors, even if they are not visual-manual tasks.

One factor that can increase a task's engagement is how interesting that task is perceived. Horrey and colleagues (2017) manipulated the interestingness of news articles to manipulate a drivers' engagement in an auditory secondary task. They found increased driving variability in lane keeping and speed control for both audio conditions in comparison to a baseline no audio condition, but the interesting audio condition performed significantly slower on the critical braking task than the boring audio condition. Yet, drivers' physiological, performance, and subjective data indicated that interesting audio stimuli required fewer cognitive resources to process than boring audio stimuli. This mirrors another study that found increased learning when reading an interesting text compared to a boring text, even though less attention was allocated to the interesting verse (Shirey & Reynolds, 1988). Currently, it is unclear how increasing engagement in a task through interestingness could influence a drivers' ability to process various streams of information and anticipate road hazard.

The process of regulating one's attention in the presence of multiple possible tasks is theorized to be a complex task requiring strategy and attentional resources (Norman & Shallice, 1986; Schumacher et al., 2001). A drivers' perception of their environment can influence how a driver decides their attention allocation strategy. For example, one study explored how drivers strategized their engagement in a secondary task while piloting either manual or partially automated vehicles. Factors such as perceived event rate and urgency level of the hazard highly affected a driver's attention allocation policy (Lin et al., 2019). Specifically, if a hazard was expected to occur more frequently, and those hazards expected to be of a higher risk, the driver would spend more time allocating attention to scan the environment and anticipating those hazards. In addition, when the hazard was deemed urgent, drivers would disengage from their secondary task but when the hazard was deemed less urgent, drivers would instead engage in task-switching. Drivers' propensity to engage in task-switching under low urgency is also demonstrated in another study that found drivers would complete a secondary texting task even after receiving a TOR from the automated vehicle (Wandtner et al., 2018). The drivers had eight seconds to respond and the response to the TOR did not require an immediate maneuver, lowering the urgency of the hazard. The perceived nature of hazards from the environment seems to be a critical component to how drivers allocate their attention in a partially automated vehicle, as predicted by Yamani and Horrey (2018). To determine one's level of risk within the driving environment, a driver must understand the relationship between themselves and their environment. More specifically, they must calibrate their own abilities to the demands and challenges of a dynamic driving environment.

Calibration

Calibration can be defined as the difference between an objective measure of an ability or skill and its subjective appraisal (Horrey et al., 2015; Roberts et al., 2016; Unverricht et al., 2018b; 2020). Ideally, there would be no difference between one's subjective self-appraisal and the objective measure of their ability or skill of interest. In such a case, one would have perfect calibration where their appraisal of their own performance perfectly matches with the actual performance. Imperfect calibration would occur when one overestimates or underestimates their performance. For example, if someone were to perform poorly on an exam and receive a 60%, yet they believe they received a much higher 80%, that individual would be overestimating their performance on that exam. Conversely, if that student instead performed well on an exam and received an 80%, but they believe they received a 60% on the exam, they would be underestimating their abilities. Both underestimation and overestimation of driving abilities can disrupt safe driving (Deery, 1999; Kuiken & Twisk, 2001).

Calibration is often studied under the field of self-appraising research. Individuals can be poor at self-appraising their own abilities (Dunning et al., 2004; Stajkovic, & Luthans, 1998; Woodman & Hardy, 2003). In general, individuals are more likely to overestimate their own abilities when compared to their peers. This overestimation has been coined optimism bias and self-enhancement bias by researchers in domains such as medicine and sports (Zell & Krizan, 2014).

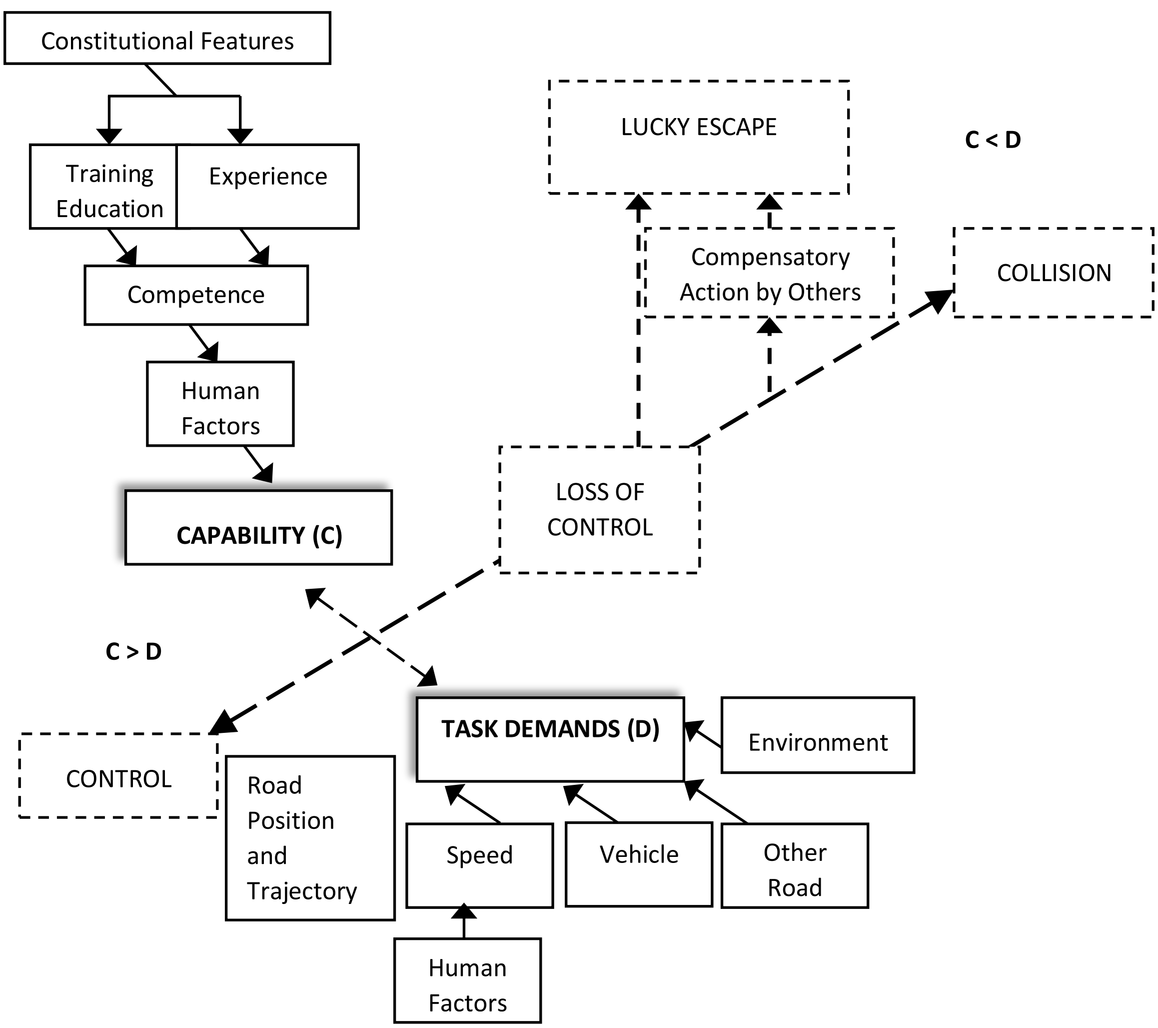
Within the domain of surface transportation, evidence consistently shows that drivers overestimate their own abilities (Amado et al., 2014; Deery, 1999; Freund et al., 2005; Horswill et al., 2004; Svenson, 1981; Roberts et al., 2016; Unverricht et al., 2018b; 2020). For example, 95% of drivers in one study rated their own abilities to be better than their actual performance

(Amado et al., 2014). Another study recruited 152 older drivers and found that 65% rated themselves as better than their peers (Freund et al., 2005). Young drivers overestimate their driving abilities even more than older experienced drivers (De Craen et al., 2011; Horswill et al., 2004; Horrey et al., 2015). A longitudinal study found that young drivers' calibration did not improve after their first two years of driving, indicating that even with two years of experience they still overestimated their abilities (De Craen, 2010). Young drivers' overestimation of their driving skills is especially dangerous as it is expected to be positively correlated with young driver crash risk (Gregersen, 1996; Mathews & Moran, 1986).

The Task Compatibility and Interface Model (TACM; Figure 3) explains how drivers adjust their behaviors to balance their driving demands with their self-assessed abilities (de Craen, 2010; Fuller, 2005; Horrey et al., 2015). Specifically, if the demands of the driving task are less than the drivers' capabilities, then the driver will maintain control. However, if the demands of the driving task exceed that of the drivers' capability, then the driver will likely lose control resulting in either a collision or a lucky escape (Fuller, 2005). TACM assumes a demand regulation theory that postulates that a driver has an internalized optimal relationship between capability and task-demands and will adjust their behaviors to achieve and maintain this relationship. Therefore, if a driver feels that the primary driving task is far beneath their capacity, and they would be able to add in a secondary task without losing control, such as texting or another NDRT. But, if the road environment demands careful vehicle control, such as being novel or obscured by rain, snow, or other types of distractors on road, the driver might adaptively slow the vehicle and lower the radio to minimize any extra demands to maintain the balance of capability and demands. For a driver to execute a safe and successful drive, they must be able to regulate their task demands with their own abilities and have an accurate estimate of both. Poor calibration can result in adopting task-demands that exceed capabilities, increasing the drivers' crash risk (Deery, 1999). Automation, while providing an avenue to improve safety by reducing task demands below the driver's capability, also provides an avenue to mis-represent task demands allowing the driver to allocate attention away from safety critical tasks like anticipating hazards and towards non-driving related tasks.

Figure 3

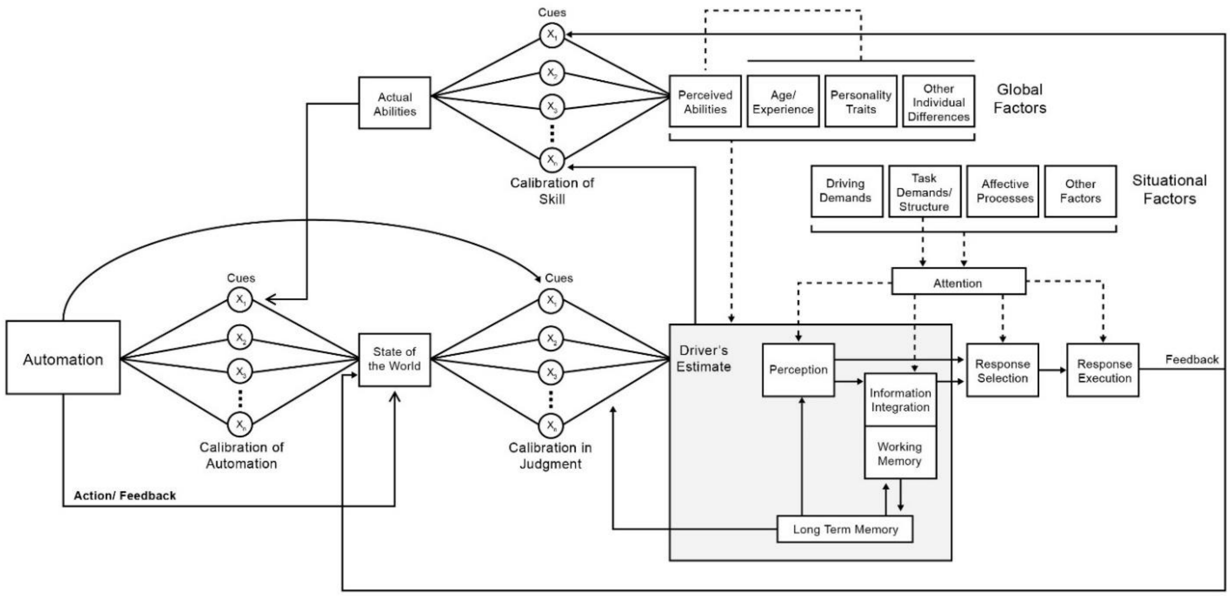
The Task-Capability Interface Model (de Craen, 2010).



The Driver Calibration Framework (DCF; Horrey et al., 2015) was proposed building on models such as TACM's demand regulation (Fuller, 2005), Wicken's HIP model (Wickens et al., 2015), and the LENS model for information selection and application (Brunswik, 1955). A main component of the DCF is that a drivers' perspective of their current performance and the state of the world is impacted by the flow of information that they process from selection, processing, integration, to response selection and execution (Figure 4). Feedback from this process feeds back into the drivers' perceptions of both their current performance and the state of the world, indicating feedback as a critical element for good calibration. Drivers who are overconfident in their abilities may be more likely to engage in distracted driving (Lesch & Hancock, 2004). Drivers who are overconfident in their abilities are less adaptive to task demands than well calibrated drivers (de Craen, 2007). Moreover, a driver that is unaware of the performance decrements caused by a distraction can be less likely to disengage from a secondary task while driving (Horrey et al., 2017).

Figure 4

The Driver Calibration Framework with the added automation component (Horrey et al., 2015).



Self-monitoring, the assessment of one's own performance or ability (Snyder, 1979), is theorized to be a central executive process, one that can elicit a high cognitive load (requiring working memory space and attentional capacity) on the individual (Donders, 2002). In this case, calibration can be considered as the ability to monitor and accurately perceive self-performance and the effects of that performance against an expected outcome. For LHA, calibration is the difference between their perception of correctly anticipating a latent hazard and their objective performance for correctly anticipating a latent hazard. Meaning, a driver who is well calibrated to their LHA performance is more accurate in determining whether or not they correctly anticipated a hazard. Automation holds the potential to "free up" attentional resources, which the driver can allocate to their self-monitoring process and theoretically increase the accuracy of their own estimated performance. However, other factors such as a highly demanding task and increased driving demands can pull attention away from the estimation process, preventing the driver from being accurately calibrated. Currently, it is unknown exactly how LOA would affect a drivers' ability to calibrate their own LHA performance.

CHAPTER III

CURRENT STUDY AND HYPOTHESES

Currently, it is unknown how the interestingness of a secondary stimuli affects a driver's LHA and their calibration of their LHA performance while piloting a partially automated vehicle. Samuel and colleagues (2020) found higher levels of automation *reduced* LHA performance, suggesting that this effect may have been caused by drivers allocating their attention away from the driving task. Horrey and colleagues (2017) found interesting auditory stimuli impaired drivers' brake reaction time more than boring auditory stimuli, and drivers reported interesting stimuli more engaging. However, the interesting stimuli required fewer cognitive resources to process than boring stimuli as measured by physiological, performance, and subjective data. Therefore, drivers in the high automated and interesting auditory stimuli condition are expected to have the greatest available attentional resources. This project aims to examine whether drivers will allocate those resources towards LHA as predicted by the Yamani and Horrey (2018) model and how LOA and task engagement may affect LHA performance.

Hypothesis 1. Drivers piloting higher levels of automation would anticipate a greater proportion of latent hazards than those piloting lower levels of automation. More specifically, drivers with the interesting auditory stimuli and in the highest level of automation condition (L3) would anticipate the greatest proportions of latent hazards.

Hypothesis 2. Drivers in the L3 condition would anticipate a greater proportion of latent hazards compared to those in the L2 and L0 conditions.

Hypothesis 3. Drivers in the interesting auditory stimulus condition are expected to anticipate a greater proportion of latent hazards compared to those in the boring auditory stimulus condition.

Hypothesis 4. Drivers piloting the L3 automated vehicle will recognize more auditory stimuli than those piloting L2 or L0 vehicles. Specifically, drivers in the L3 automation and the interesting stimuli condition would recognize the greatest proportion of auditory stimuli.

Hypothesis 5. Drivers in the L3 condition would recognize the greatest proportion of auditory stimuli compared to those in the L2 and L0 conditions.

Hypothesis 6. Drivers would recognize interesting auditory stimuli more correctly than those of boring stimuli.

CHAPTER IV

METHOD

Design

This study employed a 3 x 3 mixed-factor design with Level of Automation (L0, L2, & L3) as a between-subject factor and Interestingness (boring, neutral, & interesting) as a within-subject factor.

Independent Variables

Level of Automation

For the L3 and L2 condition, the lateral control and longitudinal velocity of the vehicle was controlled by the simulated automated driving system. Drivers in the L3 condition were instructed to monitor the automation which is controlling the vehicle. Drivers in the L2 condition were instructed to monitor the automation and their driving environment. Participants in both conditions were instructed to be prepared to take over control of the vehicle if necessary. For the L0 condition, drivers manually controlled the vehicle. L0 drivers were instructed to monitor their driving environment and control the vehicle.

Interestingness of Auditory Stimuli

Auditory stimuli consisted of news stories that varied in being either boring, neutral, or interesting. The stimuli were generated and validated in a previous work (Horrey et al., 2017). The current work used a selected set of 9 audio clips representing three interesting, three boring, and three neutral clips out of the total of 73 original stimuli recorded. To ensure that the difference between interesting and boring audio clips remained stable for this study’s population, a pilot study was conducted. Thirty-nine undergraduate students rated a set of 39 auditory stimuli for their level of engagement on a slider from -7 (*boring*) to 7 (*interesting*) in Qualtrics. The stimuli were the same news sources that were used in Horrey and colleagues (2017). All clips were presented to each participant in a random order. The pre-selected highly interesting audio stimuli (M = 2.27, SD = 2.51) were rated as more interesting than pre-selected boring stimuli (M = -1.62, SD = 2.40), $t(38) = -10.091$; $p < .001$, validating the previous study using the undergraduate student population at Old Dominion University. Neutral stimuli were presented that were neither interesting nor boring, (M = 0.01, SD = 0.04).

Dependent Variables

Latent Hazard Anticipation

LHA was operationalized as glances towards a pre-determined target zone from a pre-determined launch zone (Pradhan et al., 2005). The target zone is a pre-determined location where a hazard may materialize. The launch zone is a pre-determined location where the driver should glance towards the target zone. Only glances towards the target zone while in the launch zone will be marked as a successful anticipatory glance (Figure 1). To compute a LHA score, gaze locations were manually coded by the researcher from eye tracking videos to analyze anticipatory glances as either 1 (*successful*) or 0 (*unsuccessful*). Previous studies have used and validated this measure (for a review see Unverricht et al., 2018a).

Recognition of Auditory Stimuli

To measure retention of auditory stimuli, a procedure following that found in Horrey and colleagues (2017) was followed. Participants were presented with transcripts of all 9 auditory stimuli they had heard with an additional 9 unheard news stories that served as distractors (Appendix A). Participants were asked “Please read the following transcripts and indicate whether or not you heard each passage during the experiment by clicking yes or no." Then, participants were exposed to one of the transcripts, in a randomized order, until they completed all 18 transcripts. The total percentage of correctly identified stimuli and correctly rejected distractors served as the measure for recognition of auditory stimuli.

Driver Calibration

Calibration score was calculated using the normalized difference scores method (Roberts et al., 2016; Unverricht et al., 2018b; 2020). This method required two steps. First, normalizing the objective and subjective scores using the following formula: 100 x (score – min(score) / max(score) – min(score)). Second, calculating the difference score from the previously normalized scores. For LHA, scores were first normalized using the formula listed above. Then, the normalized objective performance (proportion of trials with a successful anticipation) was subtracted from the normalized subjective performance as measured through the calibration questionnaire. Therefore, the following formula was used to calculate the difference score: calibration = normalized subjective LHA score – normalized objective LHA score. If drivers overestimated their LHA performance, then their calibration score was positive. If instead drivers underestimated their LHA performance, then their calibration scores were negative. The better calibrated a driver was, the closer their subjective performance was to their objective performance and the closer their calibration score was to zero.

Participants

Forty-two young drivers were recruited from the community of Old Dominion University. Each participant was randomly assigned to one of the three conditions, the L0, L2 or L3 conditions. Fourteen participants were assigned to the L0 manual driving condition (nine males, mean age = 19 years, *SD* = 1.18, mean months since licensure = 26.74, *SD* = 9.44), 14 participants were assigned to the L2 partially automated condition (seven males, mean age = 19.64, *SD* = 1.01, mean months since licensure = 26.57, *SD* = 6.60), and 14 participants were assigned to the L3 automated condition (six males, mean age = 19, *SD* = .88, mean months since licensure = 25.80, *SD* = 10.73). To participate in this study, all drivers must have held a valid drivers' license, had normal or corrected-to-normal visual acuity, been a native English speaker, and had no hearing disability or any other reason that they may not have been able to comprehend the auditory stimuli. Additionally, drivers were selected from ages 18 to 21. They received either research credits or paid compensation for their participation. Compensation was paid at the rate of $10 for the first hour and $5 for every half hour completed thereafter, with a potential total of $20 per session.

Apparatus and Materials

Driving Simulator

The RDS – 1000 driving simulator (Real-time Technologies, Inc.) is a high-fidelity single seat quarter cab design that will be used in this experiment (Figure 5). The simulator was equipped with a steering subsystem, brake and acceleration pedals, and a fully customizable touch-screen center stack and a dashboard. In addition, the simulator had a 5.1 surround sound speaker for simulating environmental noise and presenting the auditory stimuli for the in-vehicle task. Three 65" screens presented the simulated roadway environment and provided a horizontal field of view at 205° and a vertical field of view at 38°. This simulator supported automated driving capabilities.

Figure 5

The RDS – 1000 driving simulator (Real-time Technologies, Inc.) driving simulator.

Eye Tracker

To record participant's eye movements, a head-mounted Pupil Core Mobile Eye tracker was used (Pupil Labs). The eye tracker simultaneously records the external scene while tracking the users' eye movements at a sample rate of 200 Hz using an infrared light. Using Pupil Capture software, the eye image and scene image are interleaved producing a crosshair indicating the driver's gaze on the scene image.

Briefing Instructional Pamphlet

To ensure that all participants have sufficient knowledge to engage in the process of anticipating hazards, they read a three-page instruction (Appendix B). The instruction manual outlined what a latent hazard is and provided an example of a precursor of a latent hazard. In addition, the instruction sheet gave the participant a brief overview of the simulated automated driving system (ADS). Specifically, it instructed the participant that the ADS can modulate, control, and maintain speed, lane deviation, but cannot anticipate latent hazards as well as how take-over requests (TORs) are issued, and how to take over when a TOR is issued.

Auditory Stimuli

The audio clips used in this study contain content of news stories either collected or generated by Horrey and colleagues (2017; Appendix A). The 9 selected stimuli represent the most interesting (M = 4.62, SD = .54), boring (M = -3.87, SD = .41), and neutral stimuli (M = .01, SD = .11). The interesting set of audio clips scored higher than the boring set across three metrics, length of audio clip in seconds (Interesting, M = 36.00 seconds, SD = 5.29; Boring, M = 23.00 seconds, SD = 6.00), objective difficulty as measured by the Flesch-Kincaid scale (Interesting, M = 24.12, SD = 13.94, Boring, M = 17.93, SD = 5.28), and word count (Interesting, M = 99.00, SD = 15.09, Boring, M = 69.33, SD = 10.69).

Simulator Sickness Questionnaires

Participants were screened for their susceptibility to simulator sickness using two questionnaires, the Motion Sickness Susceptibility Questionnaire (MSSQ; Appendix C, Golding, 1998) and the Simulator Sickness Questionnaire (SSQ; Appendix D, Kennedy et al., 1993). If participants scored above a 19 on the MSSQ, then they were not eligible to participate in this study because of their high-risk for simulator sickness. No participants scored above a 19.

Calibration Questionnaire

To measure a drivers' calibration of their own performance, four questions were asked. Specifically, participants were asked to rate their performance on a ruler Likert scale from 1 (*poor*) to 10 (*excellent*) across four metrics depending on their assignment to the L0, L2, or the L3 condition (Appendix E).

Driving History Questionnaires

Before the participant was dismissed, they filled out a driving history questionnaire which collected their demographics and driving history (Appendix F).

NASA-TLX

To explore drivers' workload, the NASA-TLX was given (Hart & Staveland, 1988). The NASA-TLX is a subjective measure of an individual's workload across several components, temporal, physical, and mental demand, performance, effort, and frustration. These components are measured through six single-item questions such as "how hard did you have to work to accomplish your level of performance?" and "how mentally demanding was the task?". Participants can respond by marking a line on a twenty-point ruler scale ranging from low to high or good to poor for one catch item (*Performance*). The NASA-TLX has demonstrated high convergent, concurrent, and internal validity (Rubio et al., 2004). Additionally, the questionnaire has demonstrated high test/re-test reliability (Hart & Staveland, 1988).

Driving Scenarios

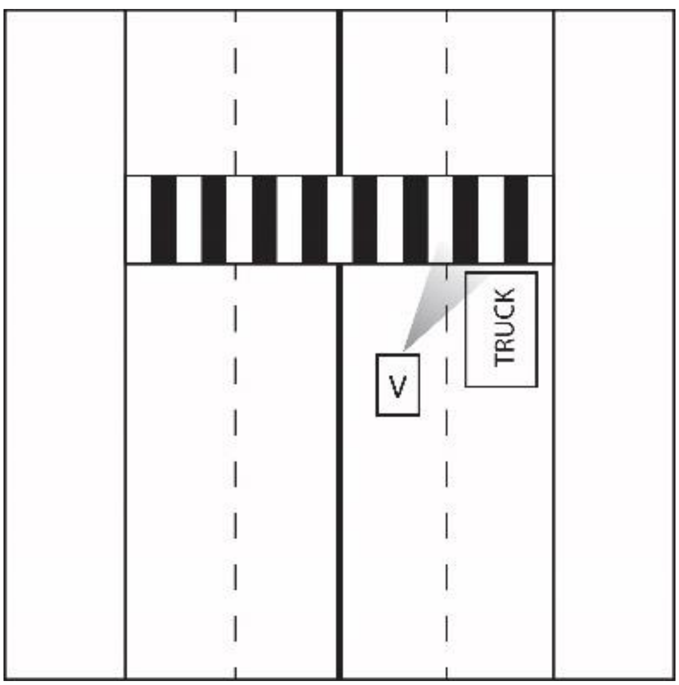
Nine latent hazard scenarios were created based on previous research (Samuel et al., 2020; Yahoodik & Yamani, 2021). Each scenario included one latent hazard event, was approximately 6,000 ft in length, and took approximately 4 minutes to complete. The onset of each auditory stimulus occurred before the participant entered the launch zone and the end was after the latent hazard event. Specifically, the vehicle traveled through a spatial trigger at a pre-determined location in the simulation, triggering the auditory clip to start playing. Following the onset of the auditory stimulus, the vehicle continued to travel before approaching the latent hazard event. After passing through the launch zone of the latent hazard event, the auditory stimulus continued to play until it reached the end of the clip. To account for order effects, the order of the 9 scenarios and the combination of the scenario and the auditory stimuli were randomized.

Potential Pedestrian at Crosswalk Hidden due to Truck

The participant is on a 4-lane road (two in each direction) and passes a traffic sign indicating a pedestrian crosswalk ahead (Figure 6). A truck and car are parked before the crosswalk, obscuring the drivers view of a potential pedestrian who might be waiting to cross. The participant should look at the area of the crosswalk immediately in front of the truck as they approach the crosswalk.

Figure 6

Potential pedestrian at crosswalk hidden due to truck.

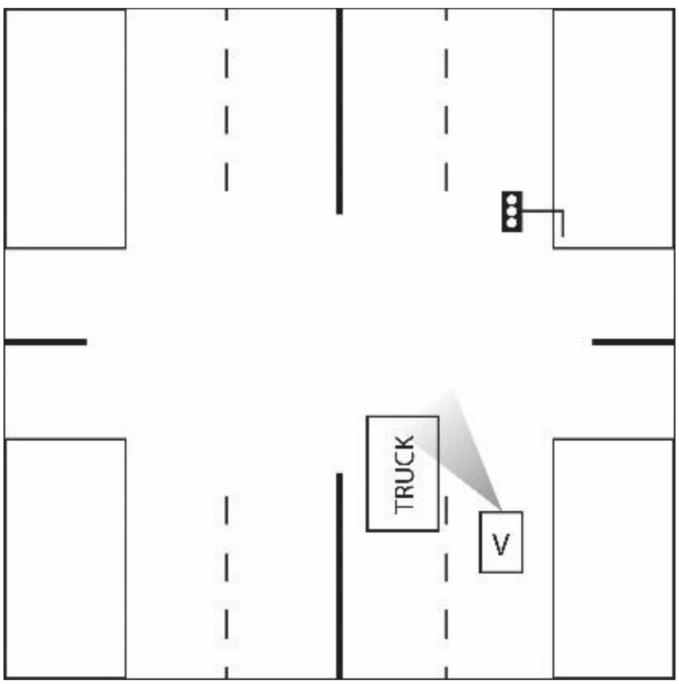


Adjacent Truck Intersection

The participant is on a 4-lane road (two in each direction) and driving straight with side streets on the right and left (Figure 7). A truck is parked in the left lane at a four-way intersection, preventing the driver from seeing any vehicles that may be about to pass in front of them. The participant should look towards the area in immediately in front of the truck as they approach the intersection.

Figure 7

Adjacent truck intersection.

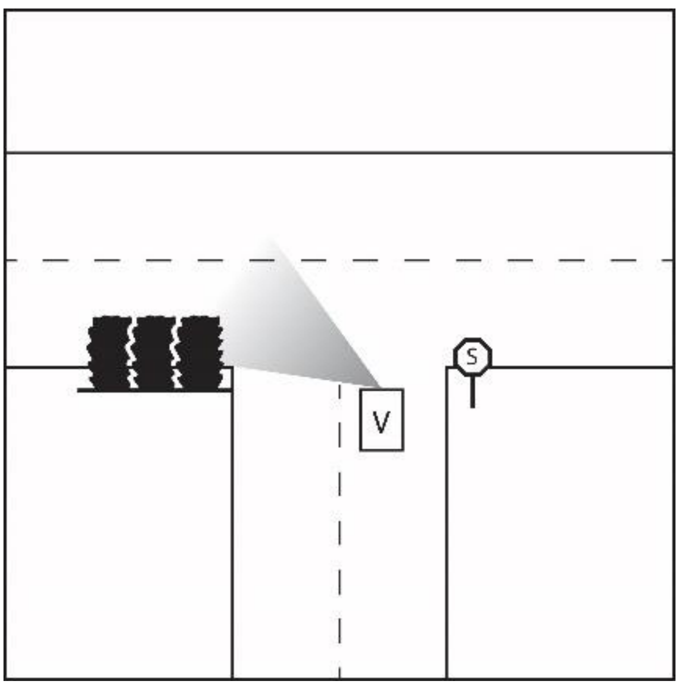


Hedge and Crosswalk

The participant travels on a 2-lane road and approaches a stop sign-controlled intersection (Figure 8). After a full stop, thick hedges block any pedestrians or vehicles that may be about to pass in front of them. The participant should look towards the area immediately in front of the hedges before they drive past the stop sign.

Figure 8

Hedge and crosswalk.

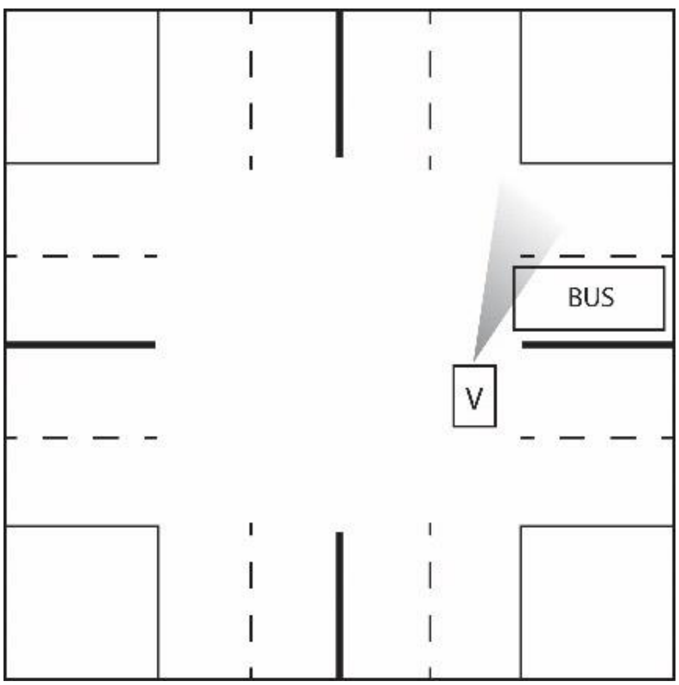


Multiple Lane Intersection with Bus

The participant is on a 4-lane road and approaches a signal-controlled intersection (Figure 9). A bus is to their right, stationary in the left-hand lane, obscuring any vehicles that may pass in front of them into the intersection. The participant should look towards the area immediately in front of the bus on their right as the approach the intersection.

Figure 9

Multiple-lane intersection with bus.

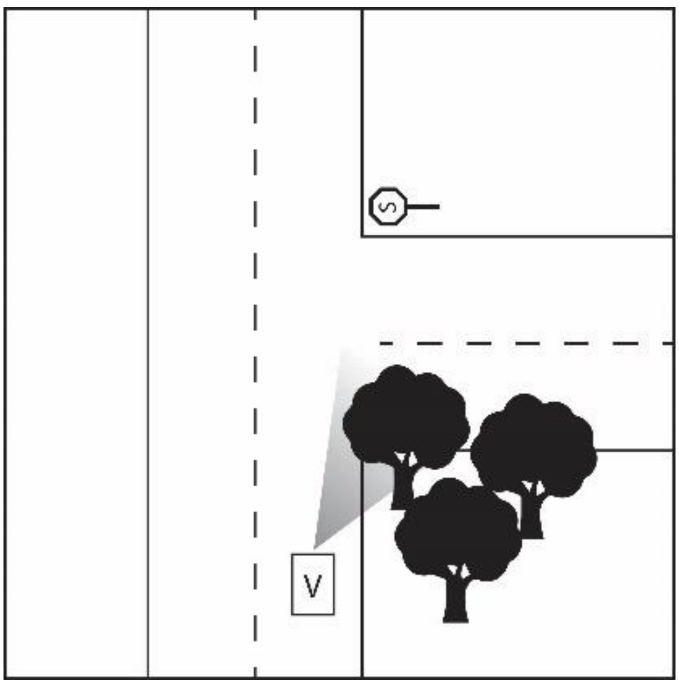


T-Intersection

The participant is on a 2-lane road with one travel lane in either direction (Figure 10). As they approach a T-intersection, trees obscure any oncoming vehicles from the right road. The participant should look towards the entryway of the right lane immediately in front of the trees.

Figure 10

T-intersection.

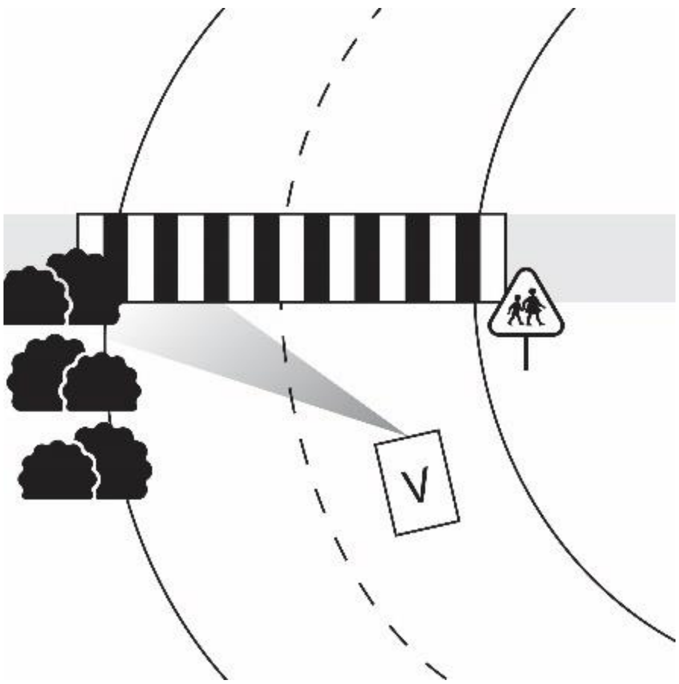


Midblock Crosswalk

The participant is on a 2-lane road and in a school zone (Figure 11). At the apex of the winding roads, vegetation obscures the left entrance to a crosswalk. Participant should look towards the hedges.

Figure 11

Midblock Crosswalk.

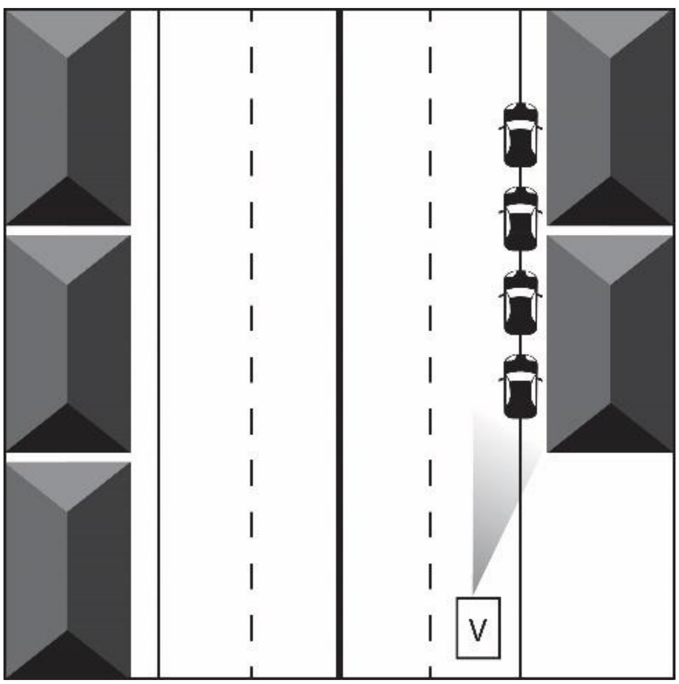


Potential Parked Car Entering the Right Traffic Lane

The participant is on a 4-lane road and is traveling on the right most lane (Figure 12). A fleet of cars are parked on the right side of the lane. To prevent a rear-end collision, the participant should look towards the line of parked cars as they approach.

Figure 12

Potential parked car entering the right traffic lane.

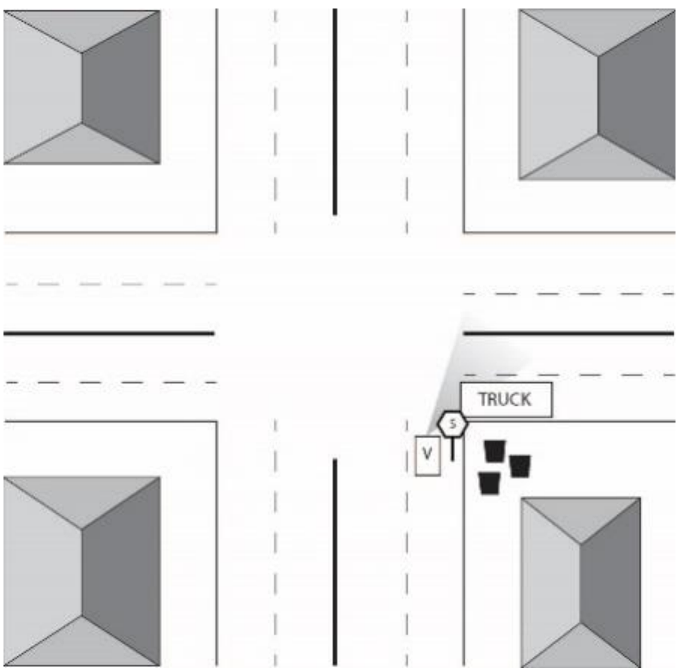


Potential Traffic Blocked by Urban Objects

The participant is on a 4-lane road and is approaching a stop sign controlled intersection with the intersecting road not controlled by a stop sign (Figure 13). Multiple trash bins and a truck prevents the participant from seeing any oncoming traffic on the right. The participant should look towards the back edge of the truck as they enter the intersection.

Figure 13

Potential traffic blocked by urban objects.

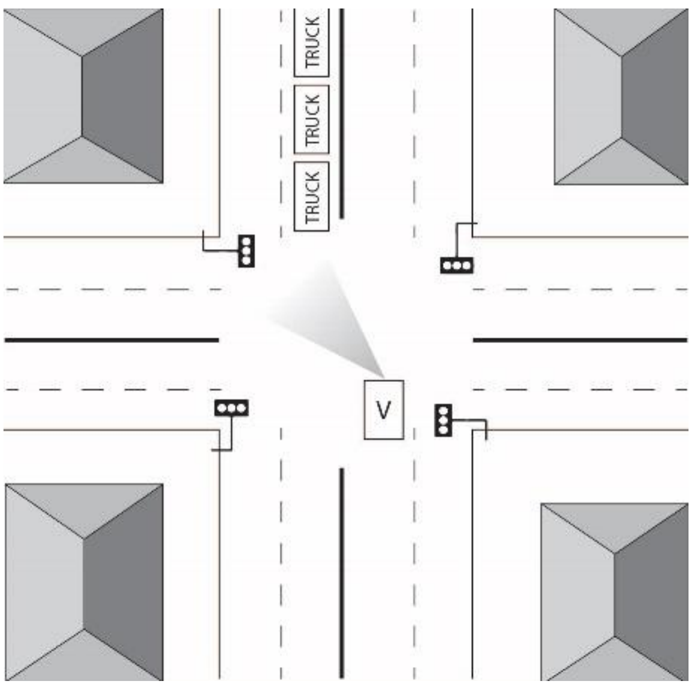


Left Hand Turn Within Intersection

The participant is on a 4-lane road and is approaching a stop light-controlled intersection with a row of trucks waiting for the lead truck to turn left (Figure 14). The row of trucks prevents the participant from seeing any oncoming traffic from the left of the trucks. The participant should look towards the area in front of the trucks.

Figure 14

Left-hand turn within intersection.



Driving Task

For the main driving task, all participants were instructed to follow the rules of the road and the posted sign limits. Participants were instructed via the briefing instructional pamphlet (Appendix B) on latent hazard anticipation and that the ADS would control all lateral and longitudinal facets of driving and it is the participant's responsibility to take over control of the vehicle if the ADS fails. Additionally, participants in the L2 condition were asked to constantly monitor both the driving environment and the ADS per SAE standards for L2 systems (SAE, 2021). Drivers in the L3 condition were asked to monitor the automation. Both automated conditions (L2 & L3) were asked to be prepared to take-over control of the vehicle if it requires. All participants were instructed that they were responsible for the safety of the vehicle, and should they drive in a manner that negatively affects the safety of the vehicle, they will have to repeat the drive."

Auditory Task

Participants were exposed to auditory stimuli that was either interesting (*high engagement*), neutral (*medium engagement*), or boring (*low engagement*). Participants were instructed that they were required to take a recognition test of the auditory clips at the end of the experiment.

Procedure

Participants read an informed consent sheet and indicated their participation if they agreed, followed by the filling out the MSSQ. If they scored lower than 19 on the MSSQ, participants continued the experiment by completing the SSQ. Then, participants were randomly assigned to one of three groups, L0, L2, or L3. All groups then read the briefing instruction manual and were prompted to ask a question, if any, to the experimenter. All participants then completed a practice drive. For those in L0, they manually drove the vehicle during the practice drive. For those in L2 and L3, the ADS controlled all lateral and longitudinal movements during the practice drive. During both the L2 and L3 practice drives, the vehicle performed a TOR requiring the driver to take control of the vehicle. After the practice drive, participants were outfitted with a head-mounted eye tracker and calibrated using the standard nine-point calibration system. For experimental drives, all drivers drove through nine simulated driving scenarios (3 containing interesting audio clips, 3 containing neutral audio clips, and 3 containing boring audio clips), in a randomized order, while having their eyes tracked. After each drive, the participant completed the NASA-TLX. After completing all experimental drives, the drivers filled out a post-simulator sickness questionnaire, calibration questionnaire, auditory stimuli recognition test, demographics questionnaire, and a driving history questionnaire.

CHAPTER V

RESULTS

Data Treatment

Histograms were generated to visually assess if the variables were normally distributed. Although the normality assumption is important in statistical analysis, ANOVA is considered robust to deviations from normality (Maxwell & Delaney, 2004, pp. 112). Levene's tests were performed to verify that the assumption of homogeneity of variance was met. The results indicated that none of the reported ANOVAs violated the homogeneity of variance assumption. To assess the assumption of sphericity, Mauchly's test was conducted to ensure that the differences in variances between all possible pairs of within-subject conditions were equal. For the majority of analyses, there were no violations to the assumption of sphericity. However, the exploratory analyses on participant's workload and the effects of Processing Depth on LHA violated the assumption of sphericity. A Greenhouse-Geisser correction was used to account for the violation in the sphericity assumption found in both exploratory analyses. Bonferroni corrections were used to account for the inflated family-wise error rate that occurs from performing multiple comparisons and reduce the likelihood of committing an inflated Type I error by dividing the alpha by the number of comparisons.

Two exploratory analyses were conducted on workload and calibration of latent hazard anticipation performance. First, workload was explored as a manipulation check. Specifically, it was to ensure that those in the manual condition indicated a higher workload than those in the automated conditions. To explore participants' workload, NASA-TLX scores were analyzed in a

3×3 mixed ANOVA with LOA (L0, L2, vs L3) serving as a between-subjects factor and Interestingness (Interesting, Boring, vs Neutral) as a within-subjects factor. Second, driver calibration was calculated using the metric used in Unverricht et al. (2018) because calibration of one's own performance is an important aspect of both the Yamani and Horrey (2018) model of human-automation interaction. To explore drivers' calibration of their LHA performance a one-way ANOVA was conducted with LOA (L0, L2, vs L3) as a between-subjects variable.

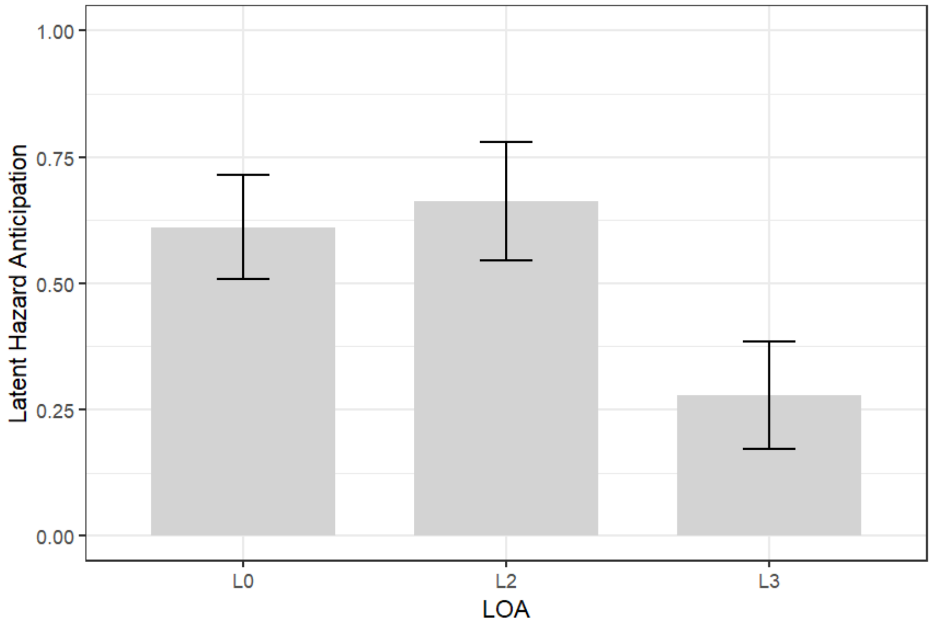
Additionally, I have extended the analysis of LHA by assessing potential effects of processing depth. Processing depth was calculated by performing a median split on the participants' LHA scores into two groups based on their scores on the auditory recognition test (high recognition vs. low recognition). To explore the added factor of processing depth, a $2 \times 3 \times 3$ mixed ANOVA with processing depth (High vs Low) and LOA (L0, L2, vs L3) as between-subjects factors and Interestingness (Interesting, Boring, vs Neutral) as a within-subjects factor.

Latent Hazard Anticipation

A 3×3 mixed ANOVA on LHA was conducted with LOA (L0, L2 vs L3) as a between subjects-factor and Interestingness (boring, neutral, vs. interesting) as a within-subjects factor. The results indicated a significant main effect of LOA, $F(2, 39) = 17.59$, $p = .02$, $\eta_G^2 = .27$. Post-hoc t-tests revealed that drivers in the L3 condition anticipated significantly fewer hazards than those in L0 condition, mean difference = .33, 95% CI = [.19, .47], independent-samples $t(26) = 4.86$, $p < .001$, and those in L2 condition, mean difference = .39, 95% CI = [.24, .53], independent-samples $t(26) = 5.35$, $p < .001$. However, drivers in the L0 and L2 conditions performed similarly, independent-samples $t(26) = .77$, $p = .44$. Note that the difference between L2 and L3 is roughly 40 percentage points, showing the effect of the manipulation on their LHA performance (see Figure 15).

Figure 15

Mean proportion of latent hazard anticipated by LOA.

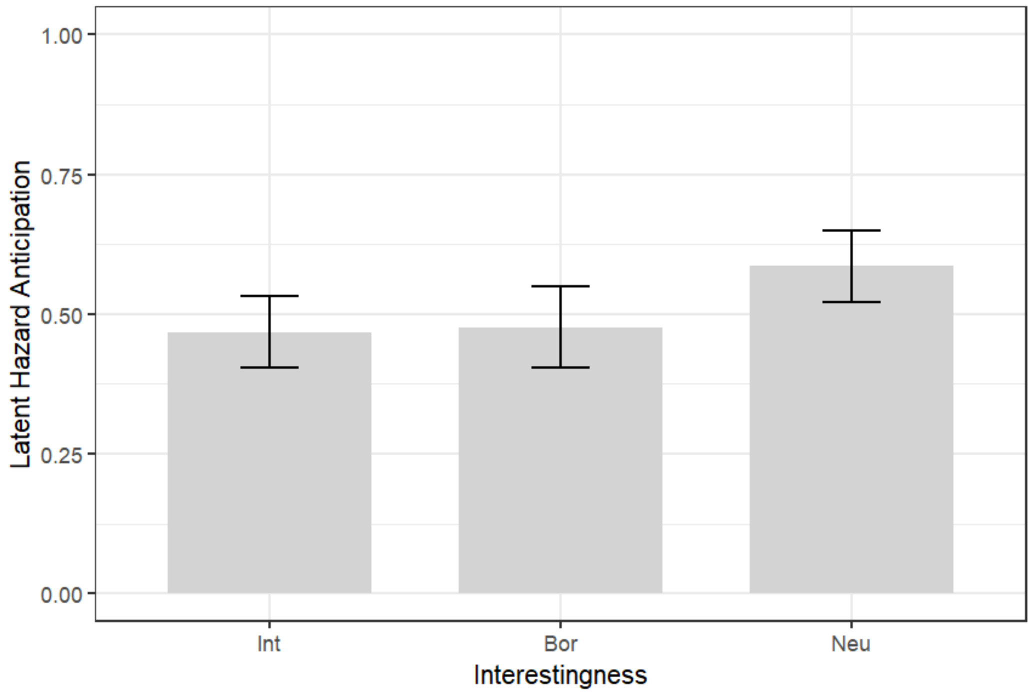


Note. Error bars represent between-subject 95% confidence intervals.

Additionally, the results indicated a significant main effect of Interestingness, $F(2, 78) = 3.67$, $p = .02$, $\eta_G^2 = .05$. Post-hoc t-tests indicated that the drivers correctly anticipated significantly more latent hazards while listening to neutral auditory stimuli than boring auditory stimuli, mean difference = .14, 95% CI = [.027, .058], paired-samples $t(41) = 2.50$, $p = .01$. Differences in latent hazard anticipation scores between the neutral and interesting auditory stimuli were not statistically reliable, paired-samples $t(41) = 2.09$, $p = .04$. The latent hazard anticipation performance were similar between interesting and boring auditory stimuli, paired-samples $t(41) = .14$, $p = .88$ (see Figure 16). No significant interaction effect was observed, $F(4, 78) = 1.58$, $p = .18$, $\eta_G^2 = .04$.

Figure 16

Mean proportion of LHA by Interestingness.



Note. Error bars represent within-subject 95% confidence intervals.

Exploratory Analysis of Depth of Auditory Processing on LHA

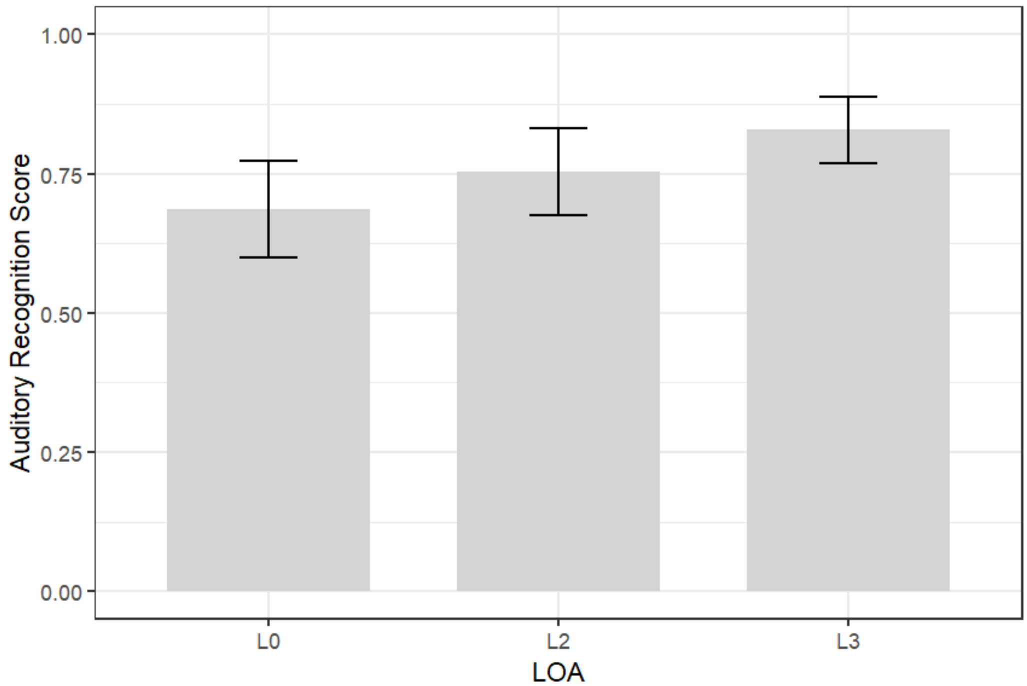
A 2 × 3 × 3 mixed ANOVA on LHA was conducted as an exploratory analysis with LOA (L0, L2 vs L3) and Processing Depth (Low, High) as between subjects-factors and Interestingness (boring, neutral, vs. interesting) as a within-subjects factor. Both main effects found in the prior 3 × 3 mixed ANOVA on LHA remained significant, Interestingness $F(2, 72) = 3.87$, $p = .02$, $\eta_G^2 = .05$, LOA $F(2, 36) = 14.80$, $p < .001$, $\eta_G^2 = .26$. However, the main effect of Processing Depth was not significant, $F(1, 36) = .76$, $p = .38$. No interactions were significant, all *p*s > .11.

Auditory Recognition Score

A 3 × 3 mixed ANOVA on participants' auditory recognition scores was conducted with LOA (L0, L2 vs L3) as a between subjects-factor and Interestingness (boring, neutral, vs. interesting) as a within-subjects factor. The results indicated a significant main effect of LOA, $F(2, 39) = 4.15$, $p < .023$, $\eta_G^2 = .11$. Post-hoc t-tests revealed that drivers in the L0 (manual) condition scored significantly lower on the auditory recognition task than those in the L3 (automated) condition, mean difference = .14, 95% CI = [-.24, -.04], independent-samples $t(26) = 2.93$, $p = .006$. Although those in the L2 condition scored roughly 6 points higher than those in L0 and 8 points lower than those in the L3 condition, scores in the L2 condition were not significantly different from those in the L0 condition, independent-samples $t(26) = 1.24$, $p = .22$, and those in the L3 condition, independent-samples $t(26) = 1.65$, $p = .10$. Figure 17 illustrates the mean auditory recognition scores by LOA. The main effect of Interestingness and the interaction effect was not significant, both *p*s > .36.

Figure 17

Mean Auditory Recognition scores by LOA.



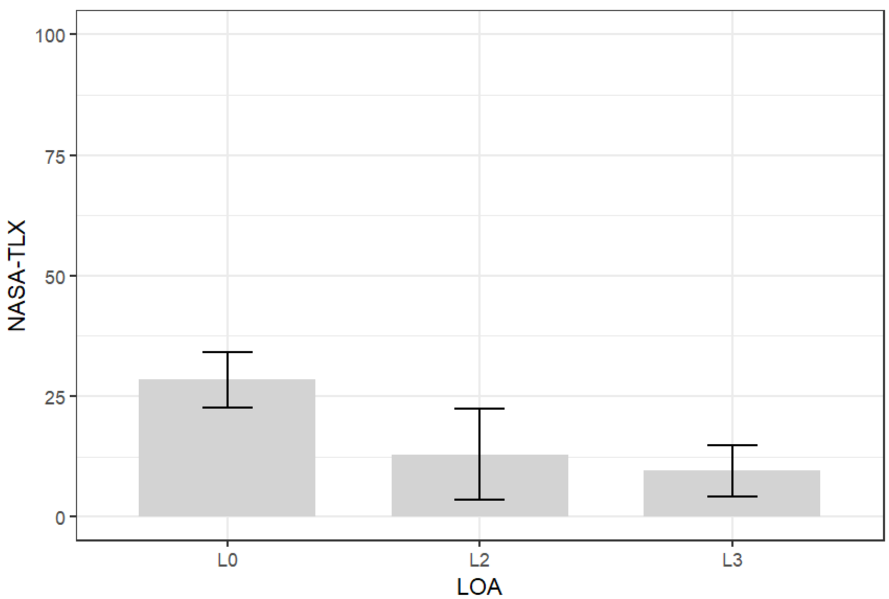
Note: Error bars represent between-subject 95% confidence intervals.

Exploratory Analysis of Workload: NASA-TLX

To explore the effect of LOA and Interestingness on participants' subjective workload, a 3×3 mixed ANOVA with LOA (L0, L2 vs L3) as a between subjects-factor and Interestingness (boring, neutral, vs. interesting) as a within-subjects factor was used to analyze NASA-TLX scores. The analysis showed the main effect of LOA was significant, $F(2, 39) = 9.34$, $p < .001$, $\eta_G^2 = .30$. Post-hoc t-tests revealed that drivers in the L0 condition reported significantly higher levels of subjective workload than those in the L2 condition, mean difference = 15.46, 95% CI = [4.91, 26.00], independent-samples $t(26) = 3.01$, $p = .005$, and those in the L3 (automated) condition, mean difference = 18.82, 95% CI = [11.40, 26.25], independent-samples $t(26) = 6.53$, $p < .001$. Drivers piloting L2 and L3 automation reported similar levels of workload, independent-samples $t(26) = .66$, $p = .50$. (see Figure 18). The remaining effects were not reliable, both *p*s > .59.

Figure 18

Mean NASA-TLX scores by LOA.



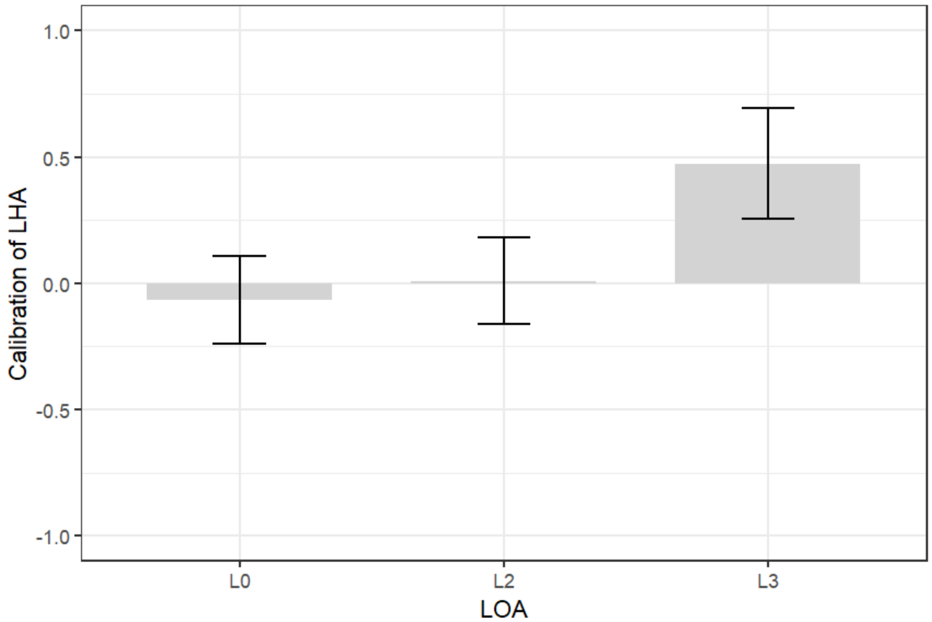
Note: Error bars represent 95% confidence intervals of group means.

Exploratory Analysis of Driver Calibration

To explore the effect of LOA on drivers' calibration of their LHA performance, a one-way ANOVA with LOA (L0, L2 vs L3) as a between-subjects factor was conducted. The main effect was significant, $F(2, 39) = 11.09$, $p < .001$, $\eta_G^2 = .36$. Drivers in the L3 (automated) condition were significantly over-calibrated to their LHA ability than those in the L0 (manual) condition, mean difference = .53, 95% CI = .80, .27], independent-samples $t(26) = 4.15$, $p < .001$, and those in the L2 (partially automated) condition, mean difference = .46, 95% CI = [.19, .72], independent-samples $t(26) = 3.60$, $p = .001$. However, differences on the calibration scores between the L0 and L2 conditions were not significant, independent-samples $t(26) = .66$, $p = .51$. Additionally, calibration scores of drivers in the L3 condition were significantly different from zero, mean = .47, 95% CI = [.25, .69], one-sample $t(13) = 4.65$, $p < .001$, indicating that drivers in the L3 condition were overcalibrated on their ability to anticipate latent hazard. On contrary, drivers in the L0 condition and in the L2 condition were not significantly different from zero, one-sample $t(13) = .81$, $p = .43$ for the L0 condition, one-sample $t(13) = .12$, $p = .90$ for the L2 condition, indicating that drivers in both the L0 and L2 condition were well-calibrated to their LHA performance. Figure 19 shows the mean calibration score by LOA.

Figure 19

Mean calibration LHA performance scores by LOA.



Note: Error bars represent between-subject 95% confidence intervals.

CHAPTER VI

DISCUSSION

This experiment aimed to expand on Samuel et al.'s (2020) study by examining the impact of LOA and Interestingness of a secondary auditory stimuli on young drivers' latent hazard anticipation, attention allocation, and calibration of their LHA performance. Theoretically, participants piloting an automated vehicle and processing engaging auditory stimuli should have had the greatest available attentional resources to deploy towards improving their LHA. Yet, it was drivers in the L0 (manual) and L2 (partially automated) groups that anticipated a greater proportion of latent hazards than those in the L3 group. This result is striking because the operational capabilities of the simulated automated driving system were identical between those of the L2 and L3 conditions. The only difference between the conditions was the presence of a particular instruction indicating that the drivers in the L2 condition had to monitor the road and the vehicle (e.g., YOU are driving) while those in L3 were instructed to monitor the automated vehicle (e.g., VEHICLE is driving). Both conditions were instructed that drivers may need to take over the control of the vehicle if the ADS cannot handle a given driving situation. This result partially corroborates with findings reported by Samuel and colleagues (2020), which employed the same manipulation in a high-fidelity driving simulator. Their participants in the L3 (automated) condition anticipated fewer hazards than those in L0. However, unlike this study, their data did not indicate reliable differences between the L2 and L3 conditions on LHA. In this study, both strikingly and alarmingly, drivers in the L3 condition performed very poorly compared to those in the L2 condition on latent hazard detection.

Furthermore, both interesting and boring stimuli impaired drivers' LHA, failing to demonstrate an effect of task engagement on LHA. The ensuing sections discuss these findings and other pertinent results in relation to prior research and hypotheses.

Auditory Recognition Test

To measure the drivers' engagement with the auditory stimuli, an auditory recognition test was given after all experimental drives. Yamani and Horrey's (2018) model predicts that higher LOA would promote greater availability of attentional resources which could be mobilized to improve performance on a secondary task. In the current study, the secondary task is the recognition and processing of auditory news clips with varying levels of interestingness (e.g., Horrey et al., 2017) presented during the section of each scenario where a latent hazard was present. Additionally, it was hypothesized that "interesting" stimuli would require less attentional resources to process and be more engaging than "boring" stimuli, as found in Horrey and colleagues (2017). Additionally, drivers in the interesting condition should thus more effectively process and recognize the stimuli than those in the boring condition. Similarly, drivers in the higher LOA were expected to recognize the greatest proportion of interesting stimuli over both those in lower LOA and boring or neutral stimuli because more attentional resources would be available in drivers in the higher LOA. Our results did not support this hypothesis. Our results only showed a main effect of LOA on auditory recognition scores. That is, as LOA increased, so did performance on the auditory recognition test. Specifically, those in the L3 condition scored significantly higher than those in the L0 condition. Surprisingly, although those in the L3 condition scored almost 8% better than those in the L2 condition, there was no significant difference between them. Those in the L2 condition were not significantly different at anticipating latent hazards as those in the L0 condition *and* were not significantly different at processing the news clips as those in the L3 condition. This finding suggests that the L2 vehicle automation may maintain driving-related performance (e.g., latent hazard anticipation) *and* improve performance on the secondary auditory task. This multitasking benefit is no longer present in the L3 condition as the LHA performance declines (see below for a more detailed analysis of the main effect of LOA on LHA). This benefit is unsurprising as it mirrors that which was predicted in the Yamani and Horrey model, but it does highlight that those in the L3 condition could have done the same but neglected to anticipate latent hazards. What is surprising is that interesting stimuli were not any more or less discernable than boring or neutral stimuli. The auditory recognition test may not have been sufficiently discriminating. Participants in Horrey and Colleagues (2017) were asked to discriminate 65 stimuli, containing boring or interesting content, and an additional set of five distractors. In this current study, drivers were asked to discriminate nine stimuli (three interesting, three boring, three neutral) and a set of nine distractors. Perhaps the differences required to attend to and process the different number of stimuli may have reduced the sensitivity of the test. For example, there may have been key terms from the news clips (e.g., tree nursery or Scheenberger) that made passages more salient to recognize, even without deeper processing.

Latent Hazard Anticipation

Previous research has demonstrated that automation can improve a drivers' performance by means such as reducing drivers' workload (Parasuraman & Riley, 1997; De Winter et al., 2014), or freeing attentional resources for situation awareness (Endsley, 1995; Parasuraman et al., 2000; De Winter et al., 2014). However, automation can also impair a driver by changing them from an active participant to an inactive supervisor leading to cognitive underload (Young & Stanton, 2002) or passive fatigue (Saxby et al., 2013) causing drivers to engage in non-driving related tasks (Carsten et al., 2012). Therefore, one goal of this study was to investigate the effect automation and interestingness of secondary stimuli had on a driver's LHA. Yamani and Horrey's (2018) model suggests that as driving tasks are automated, corresponding amounts of attentional resources, "freed" by the automation, are made available towards performing another task. In this case, theoretically, those attentional resources could have been allocated towards anticipating latent hazards, listening to or processing the auditory stimuli, or elsewhere towards a non-driving related task such as mind wandering. To improve driving performance, drivers should first allocate as many attentional resources as necessary towards the primary driving task, such as anticipating hazards, then allocate any remaining resources towards the secondary task. However, not all tasks are the same, and Horrey et al. (2017) demonstrated that interesting tasks are easier to process but may be more engaging, resulting in the misallocation of attentional resources. Ideally, higher levels of automation should result in the higher anticipation of latent hazards and interesting stimuli should be less distracting than boring stimuli. Yet, the results did not support this hypothesis. Both LOA and interestingness influenced LHA, but the effects did not interact.

As noted earlier, Samuel et al. (2020) found that drivers in the L3 condition performed worse than drivers in the L0. Furthermore, drivers in the L0 and L2 conditions showed no significant differences. Our study replicated and extended their findings where we showed drivers' latent hazard anticipation sharply declined in the L3 condition, significantly, compared to the L0 and even the L2 conditions. It is important to note that the only experimental difference between the L2 and L3 condition was the instruction. Both conditions received the identical briefing about LHA and were instructed that the ADS was incapable of performing LHA. Drivers in both conditions were also instructed to monitor their ADS and to be prepared to take over control of the vehicle at any time if necessary. But they differed as those in the L2 condition were instructed to monitor the forward roadway while those in the L3 condition were not explicitly instructed to monitor the forward roadway. This instruction may have led to those in the L3 condition disengaging from anticipating latent hazards and instead allocating an excess amount of their available attentional resources towards the auditory stimuli. Through this instruction, drivers may have changed from an active participant to a passive monitor, which can cause them to engage in non-driving related tasks (Carsten et al., 2012), or become "out of the loop" (OOTL; Cunningham et al., 2015). The removal of the physical control loop can cause a driver to engage in passive monitoring, such as failing to visually scan safety critical areas such as crosswalks at intersections (Merat et al., 2019; Seppelt & Victor, 2016). The difference in LHA between the L3 and L2 condition could be a product of L3 drivers being OOTL.

Horrey et al., (2017) demonstrated that interesting stimuli are both more engaging and easier to process. As a secondary task, interesting stimuli were expected to be the least distracting from the primary task of LHA because of the low mental demand required for processing the information. In contrast, the boring stimuli were expected to be the most distracting from the primary task of LHA because of the high mental demand required for processing the information. However, our findings did not mirror our expectations. There was little difference between the interesting and boring conditions on LHA. Both the interesting and boring conditions decreased drivers' anticipation of latent hazards in comparison to neutral stimuli. It is important to note that this effect occurred independent of the LOA manipulation, regardless of the availability of attentional resources.

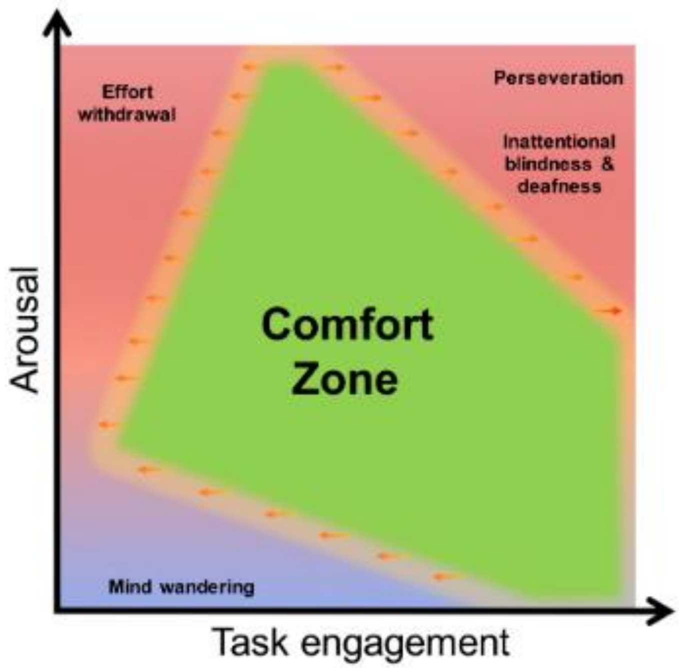
Two mechanisms may explain these results. The first mechanism is task engagement. One aspect of interesting stimuli is, although easier to process, it can be more engaging. More engaging stimuli can be easier to sustain engagement, harder to disengage, and easier to reengage with (O'Brien & Toms, 2008). When drivers were listening to the interesting auditory stimuli, they may have allocated more attentional resources than necessary to this non-driving related task. By over-engaging with the interesting stimuli, they may have misallocated resources that were necessary for LHA.

The second mechanism is task difficulty. Boring stimuli are both more difficult to process and less engaging. A task with low engagement can be difficult to sustain engagement, easier to disengage, and harder to reengage with (O'Brien & Toms, 2008). In this study, participants were instructed in a way to provide equal priorities for each task. The instruction was to ensure that they had a negative consequence for neglecting either the driving or secondary task. For the secondary task, they were instructed they would need to take a recognition test on the news clips they heard during their drives. This goal may have resulted in the drivers actively attending to the boring stimuli to improve their scores after the drives were complete. In this event, the boring stimuli would be demanding and may have unintentionally served a similar role as the interesting stimuli, attracting valuable attentional resources necessary for LHA. Again, this effect is independent from the total amount of available resources, noted through the lack of an interaction between LOA and Interestingness. Drivers' may have over-engaged in the boring stimuli, not because it was engaging, but to ensure performance after the run due to the stimuli's inherent difficulty and the upcoming recognition test.

It is possible that task engagement alone is not sufficient to explain why there were no differences between the effects of interesting and boring stimuli on LHA. Arousal can be described as an individual's state of physiological activity (Broadbent, 1971; Kahneman, 1973). These physiological activity states can range from high arousal (i.e., excitement) to low arousal (i.e., sleep). Attention and arousal involve complex psychophysiological processes with multiple dimensions that closely interact with each other, but they still retain their distinct and diverse characteristics (Coull, 1998). Like attention and arousal, task engagement and arousal are also similar but retain different processes. Dehais and colleagues (2020) mapped neurocognitive states that were predictive of degraded performance across orthogonal dimensions of task engagement and arousal (see Figure 20). For example, in Figure 20, an individual who has low arousal and low task engagement may choose to mind wander while an individual who has high arousal and high task engagement may experience perseveration. For this study, interesting and boring stimuli may have had different task engagement values (i.e., boring = low, interesting = high) but similar arousal values (i.e., both = high). Although, Figure 20 represents only one model of how arousal and task engagement may interact, arousal may have also played an important part in interestingness' effect on LHA.

Figure 20

Conceptual map of performance across arousal and task engagement.



Note. Performance is optimal across the green "comfort zone" while degraded mental states lie outside of the operators' "comfort zone" (Dehais et al., 2020).

Calibration of LHA Performance

One important aspect of Yamani and Horrey's (2018) model is the role of calibration (Unverricht et al., 2022). The DCF provides a model of the calibration process including assessment of the automation's actions, their own abilities, and the state of the world (Horrey et al., 2015). One implication of the model is that humans do not have direct access to their abilities or the state of world but instead have access to cues that can help them make assessments or estimates of each reality. The TACM framework (de Craen, 2010) describes how inaccurate assessments of one’s own abilities can result in crashes or losing control of the vehicle, indicating its importance for driving safety. In this study, as LOA increased, additional attentional resources were expected to be made available and help improve the drivers’ self-assessment of their own LHA performance. However, the results did not support this hypothesis. Instead, those in the L0 and L2 conditions were well-calibrated to their performance whilst those in the L3 condition highly overestimated their performance. There are three mechanisms that may explain these results. First, drivers in the L3 condition may have reported similar calibration ratings to that found in the L2 and L0 conditions, yet they performed much poorer skewing their perceptions. This possibility means that the calibration questionnaire used in the study might not be sensitive to potential variations in their calibration judgments. Second, those in the L3 condition may not have had any available resources left over to allocate towards the self-monitoring task. This explanation is unlikely as those in the L2 condition were well-calibrated, anticipated significantly greater latent hazards, and were not significantly worse on the auditory recognition test. Lastly, those in the L3 condition may not have allocated their available attentional resources towards the self-monitoring process, as they devoted those resources elsewhere such as towards the auditory secondary task. This explanation is supported by the L3 condition performing worse on LHA and well on the auditory recognition task. Further research is necessary to experimentally test these possibilities.

NASA-TLX - Workload

The NASA-TLX was used as a manipulation check to determine if the different levels of automation and auditory stimuli varied in workload. Theoretically, the L3 condition and interesting condition should have reported the lowest workload in comparison to the manual and boring condition. Our results did not support this hypothesis. There was no interaction between interestingness and LOA and no effect of interestingness. There are two possible explanations to explain this finding. First, although there was an urgent priority given to the secondary task through instruction of a test, listening to the secondary task was not explicitly stated to be mandatory and could have been attended to or ignored at will. Second, the instruction of the auditory recognition test may have resulted in the auditory material being attended to regardless of interestingness of the material. A main effect of LOA was found, and as expected and predicted by the Yamani and Horrey (2018) model, higher levels of automation resulted in lower subjective workload scores.

Performance Operating Characteristic Function

To explore tradeoffs between the LHA task and the auditory task, I conducted a performance operating characteristic analysis. POC is an integrated method to represent resource tradeoffs where curve positions indicate efficiency and bias of two tasks concurrently performed on a theoretical curve assuming a fixed pool of attentional resources. Figure 21 illustrates multiple points, each representing distinct biases between two tasks on a performance space, with task A represented on the Y-axis and task B on the X-axis. Point P represents a performance level of perfect timesharing as well as each performance alone. Thus, the distance of POC from the origin indicates efficiency of time-sharing resources between tasks A and B.

Figure 21

Example performance operating characteristic.

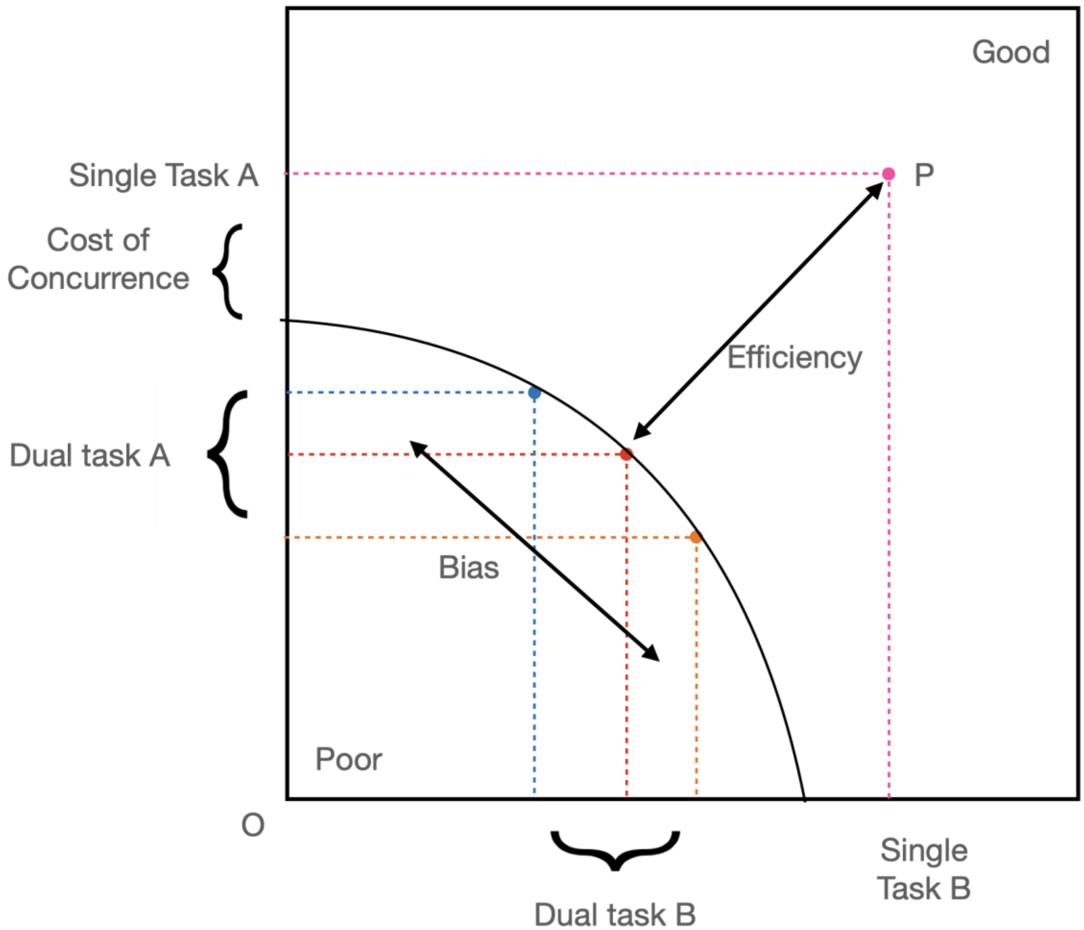
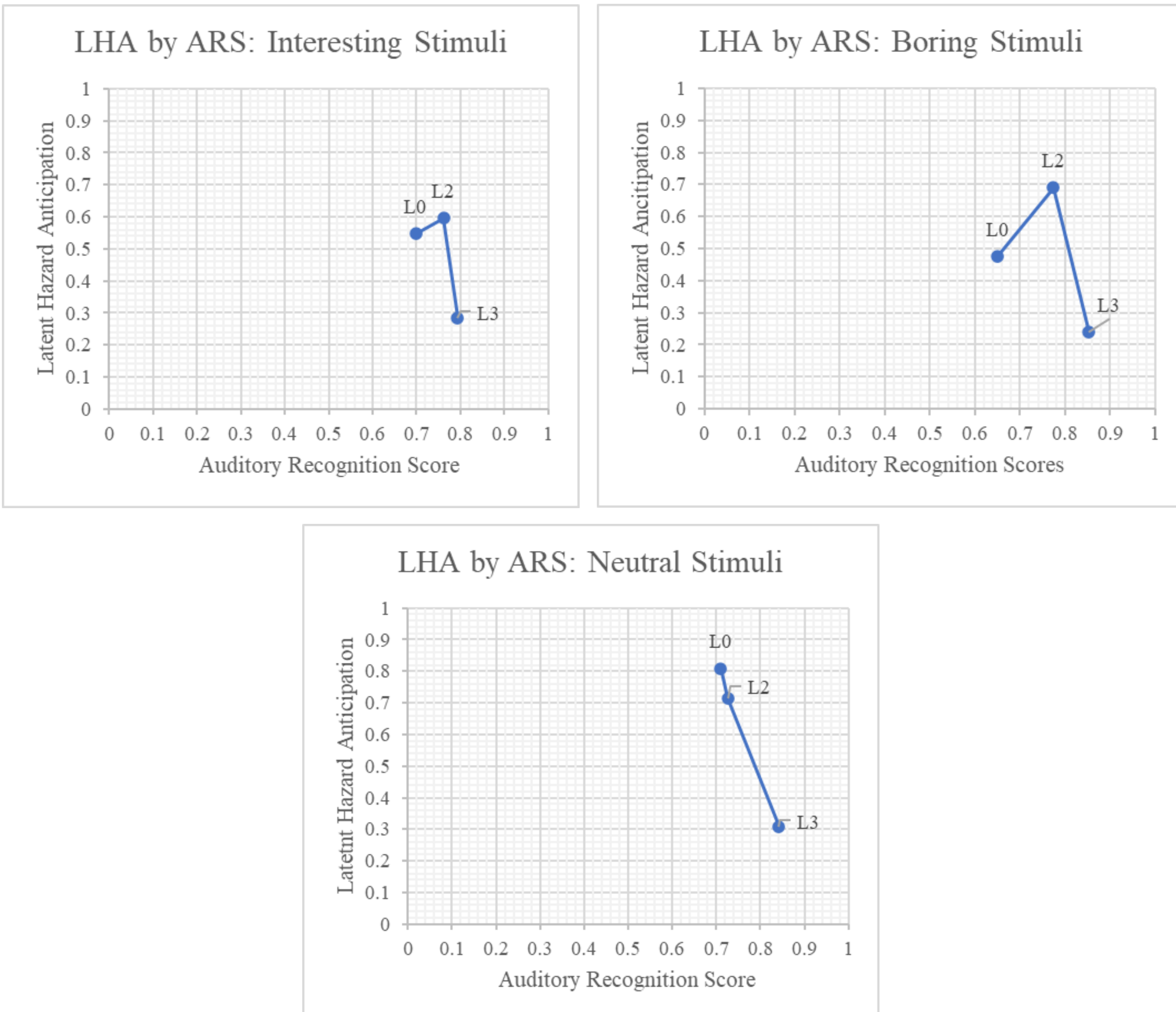


Figure 22 presents a POC function between LHA and the auditory recognition scores across LOA levels plotted separately for interesting, boring, and neutral auditory stimuli. In general, as LOA increased, there was a tradeoff between LHA and auditory recognition scores as represented as the data point diagonally shifting from the top left to the bottom right. This is a pattern indicative of allocation of limited attentional resources from performing the LHA task to the auditory recognition task, as expected by Yamani and Horrey's (2018) theoretical model of human-automation interaction.

Figure 22

POC function between LHA and auditory recognition scores across LOA levels.



Note. POC function plotted separately for the interesting (left), boring (right) and neutral (center) auditory stimuli.

Limitations

There are several limitations that should be considered when interpreting the current data. First, the secondary task in this experiment did not include explicit instructions and did not have a direct outcome variable. Specifically, drivers were instructed that the auditory clips would play during the drive and of the test, but they were not explicitly instructed to listen nor did they have to provide any direct response during the task. One could inquire if the auditory task was a task at all. However, there was strong ecological validity of the auditory task. Many secondary tasks performed during driving do not require responses because to do so may compete with the primary driving task. If participants had performed an active secondary task, such as an n-back task, their workload would have increased and there could have been greater differences in LHA found between the different levels of automation. Yet, using an n-back task would have decreased the ecological validity and generalizability of the results found in this study. An obvious extension of the current work is to ask participants to respond in some way to auditory stimuli *only if* they are able and comfortable doing so. This would effectively serve as a secondary performance measure of workload (Wickens et al., 2021). It will reduce ecological validity but could clarify an interplay between driving/piloting ADS and listening to auditory stimuli. Second, the small number of interesting and boring trials for each participant (n = 3 per participant per condition) may have interacted with the sample size making the experiment underpowered to find differences between interesting and boring stimuli. This is unlikely as the differences between the groups were marginal (< 1%) and the sample size chosen for the current study was calculated via a power analysis using the most conservative estimate of the prior Samuel and colleagues (2020) effect sizes. Additionally, the auditory stimuli were validated with the ODU student population. It is likely that other aspects of task engagement such as task difficulty may have interacted with the effects of task interest and washed away the differences between interesting and boring stimuli, but it requires further research.

Practical Applications

If attention is allocated as outlined in Yamani and Horrey's (2018) model, automation may have the benefit of allowing a driver to successfully reallocate available resources to support the driving task, but it does not appear too useful for improving a young drivers' LHA. Alternatively, automation has demonstrated an alarming cost to the driver's LHA performance. Those in the L3 condition anticipated latent hazards at rates worse than those in the L2 condition, the difference being roughly 40 percentage points. In fact, L3 drivers' LHA performance was at the same poor rate found in newly licensed drivers (Unverricht et al., 2018). Given that this effect was caused only by the instruction manipulation, inaccurate instruction on capabilities, limitations, or how to interact with the ADS, even occurring unintentionally, can cause young drivers to anticipate significantly fewer latent hazards when using vehicle. Instead of utilizing the L3 vehicle automation, other methods can be innovated and implemented such as training programs designed to improve LHA (Unverricht et al., 2018). However, if one decides to consider automation as a tool for improving, or replacing, young drivers' driving performance, user guidance for automated systems is critical to promote the drivers to establish proper mental models of ADS and effective human-automation interaction.

Additionally, as automated technologies become increasingly autonomous, understanding the psychological mechanisms underlying LHA may guide the development of artificial intelligence (AI) to support the human anticipatory process. One model explaining how humans anticipate hazards suggested that experience develops a series of schemas of driving environments in long term memory that is compared against while a driver is viewing the forward roadway (Fitzgerald & Harrison, 1999). In this explanation, a driver is actively comparing the driving environment to stored representations of similar environments they have experienced in the past, if the present environment is similar to a stored schema of a potential hazard the driver will anticipate this hazard and scan for more information. Various trainings have applied models of hazard anticipation, such as Fitzgerald and Harrison's, to improve drivers' anticipatory ability. Horswill and colleagues (2021) developed a training that provided participants with over 1000 years of accident experience, assuming an accident rate of one accident per 10 years of driving, and found trained drivers anticipated approximately 60% more hazards than the control group and demonstrated real-world transfer of the training effects. It is unknown if the drivers in Horswill and colleagues (2021) study anticipated more hazards because they developed a larger more sophisticated set of schemas to compare against or if it was because of another mechanism apparent in their training; yet this finding highlights the importance of understanding the psychological mechanisms underlying LHA. Specifically, if we understand how LHA is developed and works in humans, we may apply such understanding to an AI to help support or replace the human anticipatory process. For example, if a human can improve their anticipatory ability by watching and analyzing hundreds of hours of motor vehicle near misses and crashes, then an AI system would be able to view and analyze thousands of videos within a shorter time period, improving its anticipatory ability. AI systems that can provide some hazard anticipatory assistance are currently under exploration (Saito et al., 2021).

Theoretical Implications

The results of this study concur with models of human-automation interaction (Yamani & Horrey, 2018; Driver Calibration Framework, Horrey et al., 2015). Even though these models describe how attention could be allocated to improve performance, various factors can influence what allocation policy a driver will adopt (Kahneman, 1973). Young drivers demonstrated in this study, as well as in Samuel et al. (2020), that when faced with high levels of automation, they may adopt an attention allocation policy that impairs LHA, especially when performing a secondary task. Additionally, young drivers' LHA ability may not simply improve by the allocation of additional attentional resources. Literature suggests that, to perform LHA well, one needs a well-developed mental model (Horswill & McKenna, 2017). Some evidence demonstrates that the deployment of such mental models require cognitively demanding and resource-dependent processes. For example, McKenna and Farrand (1999) had both experienced and novice drivers identify hazards while performing a random letter generation task. Their results showed a greater interference under dual task conditions for the experienced drivers when compared to novices. In fact, the interference from the dual-task was in such magnitude that it reduced the experienced drivers' performance to that of novices. Rowe (1997) performed a similar study using a letter detection task and found no difference between younger experienced drivers and older experienced drivers, indicating it was experience causing the interference not age. Young drivers have yet developed their mental models of typical driving scenarios because they have not been exposed to such risk scenarios since their licensure. However, older more experienced drivers may have developed their mental models representing common risky scenarios, allowing them to receive greater benefits from automation by "freeing up" and reallocating attentional resources to latent hazard anticipation. However, more research is required to understand the nature of LHA and how the mental models may develop as an individual grows in both age and experience.

Future Research

Findings within this dissertation represents one step of many required to understand the complex relationship between human drivers and automated vehicles. How instructions are framed and what mental models such instructions help the drivers form may have a detrimental effect on the driver's attention and must be considered carefully. User guidance on how to interact with the automated system may be a critical component for attention allocation strategies and should be further explored. To these effects, future research is necessary for examining what factors influence drivers' attention allocation policy. For example, it is possible that the drivers in the current study adopted a resource allocation policy to prioritize the auditory task over the LHA task because they were told that they would receive a test on the auditory stimuli. Such experimental procedures might have influenced their decision on which task to prioritize more when more attention becomes available. Additionally, more research should investigate how the development of mental models in young drivers can differ between conditions with or without ADS.

CHAPTER VII

CONCLUSION

The present research examined the effects LOA and task engagement on young drivers' LHA. Additionally, we sought to explore how young drivers would allocate any attentional resources "freed" by automation when presented with a secondary task varying in engagement or interestingness. Results from this current work revealed two important findings. First, the L3 automation impaired young drivers' LHA and did not demonstrate any benefits towards improving their performance. Second, framing of user guidance for automated systems is a critical component that determines human-automation interaction involving ADS. In general, the effect of LOA on LHA replicated and extended that found in previous studies (Samuels et al., 2020; Ebadi et al., 2021), and results were generally consistent with predictions inherent in the Yamani and Horrey (2018) model. This research is one step towards understanding the complex relationship between human drivers' and automated vehicles.

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APPENDIX A

AUDITORY STIMULI AND DISTRACTORS

Boring Auditory Stimuli

- “Construction of Legacy Park is approximately 30 percent complete and is expected to be finished in fall of this year, according to the city’s most recent update of the project. Work completed to date includes the majority of the rough grading work on the park site and installation of most of the offsite storm drain infrastructure work, such as piping, catch basins and manhole structures.”
- “United Nations Secretary-General Ban Ki-moon today appointed Major General Natalio C. Ecarma of the Philippines as Head of Mission and Force Commander of the United Nations Disengagement Observer Force (UNDOF). The Secretary-General is grateful to Major General Jilke for his outstanding service and leadership of UNDOF over the past three years. Major General Ecarma is currently serving as Deputy Commandant, Philippine Marine Corps and Concurrent Commander, Marine Forces Southern Philippines. He will bring to his new position extensive and wide-ranging command experience.”
- “Sterling Speirn of San Mateo, California, has been named as the new president and CEO of the W.K. Kellogg Foundation. Speirn, who is currently the president and CEO of Peninsula Community Foundation, a leader in Peninsula and Silicon Valley community philanthropy and one of the Bay Area’s largest foundations, will replace William C. Richardson, who will retire from the Foundation December 31, 2005.”

Interesting Auditory Stimuli

- “A 48-year-old immigrant from Malta regularly hangs out in various New York City bars, but always on the floor, so that he can enjoy his particular passion of being stepped on. "Georgio T." told The New York Times in June that he has delighted in being stepped on since he was a kid. While one playmate "wanted to be the doctor, (another) wanted to be the carpenter ... I would want to be the carpet." Nowadays, he carries a custom-made rug he can affix to his back (and a sign, Step on Carpet) and may lie face-down for several hours if the bar is busy. He is also a regular at "high foot-traffic" fetish parties, where dozens of stompers (especially women in stilettos) can satisfy their own urges while gratifying Georgio.”
- “The head of Florida's Department of Corrections admitted in May that at least 43 children (including a 5-year-old), who observed their parents' prison jobs as part of "Take Your Sons and Daughters to Work Day" in April, were playfully zapped by 50,000-volt stun guns. DOC Secretary Walt McNeil said the demonstrations (in three of the state's 55 prisons) even included one warden's kid, but that only 14 children were individually shot (with the rest part of hand-holding circles feeling a passing current). Twenty-one employees were disciplined.”

- “Saskatchewan physician John Scheenberger, then 31, implanted a thin, 6-inch tube of someone else's blood in his own arm in order to beat a DNA test after two female patients had accused him of rape. He cut open his bicep, inserted the tube, and pushed it down to the crook of the arm from which blood is usually drawn. Thus, "his" DNA didn't match the rapist's, and the cases were closed. However, one victim later hired a private detective, who exposed the scam, and Berger was convicted in 1999 (though he maintained that he was forced into the deception because someone had framed him by breaking into his house and stealing a used condom).”

Neutral Auditory Stimuli

- “What a difference a day makes, Charles Wesley Mumbere, 56, was a longtime Nurses Aide at a nursing home in Harrisburg Pennsylvania. Until July, when the Uganda government recognized the separatist when Zururu territory founded in 1962 by Mumbere's late father. In October Mumbere, returned to his native country as king of the region's 300,000 subjects”
- “Saratoga Tree Nursery produces more than 50 species of trees and shrubs for planting on public and private land. The objective of the program is to provide low-cost, native planting materials from known New York sources to encourage landowners to enhance the state's environment for future generations. The Saratoga Nursery also offers a few non-native species which can enhance wildlife planting. For instance, torengo crabapple provides a winter food source for wild turkey, grouse and deer.”
- “Donny Lee Cornell was incarcerated at 3:40 am Tuesday. Authorities in cable county charged him with felony fleeing while driving under the influence along with misdemeanor leaving the scene of an accident, 1st offense driving under the influence, and no insurance according to booking records at the western regional jail”.

Distractors

- “Attorney General Eric Holder today announced the appointment of three new U.S. Attorneys to serve on the Attorney General’s Advisory Committee. The committee, which reports to the Attorney General through the Deputy Attorney General, represents the voice of the U.S. Attorneys and provides advice and counsel to the Attorney General on policy, management and operational issues impacting the Offices of the U.S. Attorneys.”
- “What a difference a day makes, four apparently quite bored people in their early 20s were arrested in September in Bennington, Vt., after a Chili's restaurant burglar alarm sounded at 4:30 a.m. According to police, the four intended to remove and steal the large chili on the restaurant's sign, using a hacksaw and power drill. However, not possessing a battery-operated drill, they had strung extension cords together running to the nearest outlet they could find, which was 470 feet away, across four lanes of highway and through a Home Depot parking lot.”
- “In November, a Chicago judge ruled that former firefighter Jeffrey Boyle is entitled to his $50,000 annual pension even though he had pleaded guilty in 2006 to 8 counts of arson and allegedly confessed to 12 more. Boyle is known locally as matches Boyle to distinguish him from his brother John quarters Boyle who is present for bribery following the theft of millions of dollars in state Tollgate coins. Judge Leroy Martin jr. concluded that matches arsons were wholly separate from his firefighting.”

- “Starling Stern, in partnership with leading organic companies from around the world, has developed a web based sustainability navigator aimed at raising consumer awareness of sustainability. The 'Sustainability Flower' empowers the consumer to make an informed purchasing decision taking all relevant environmental and ethical implications into account.”
- “United Union transit workers demanded health insurance upgrades and were agreed to by the the Southeastern Pennsylvania Transportation Authority. The upgrade will allow for the removal of the 10 tablet per month rationing of medications to allow as many as 30 per month according to Philadelphia Daily News Report. The final contract, reported to be even more beneficial to the union, was being voted on by the union members at the present time.”
- “Phillip Mathews, 73, whose logging truck is equipped with a tall boom arm to facilitate loading, forgot to lower the arm after finishing a job in Bellevue, Iowa, in October, and when he returned to the highway, the boom proceeded to snap lines on utility poles he passed for the next 12 miles until motorists finally got his attention”
- “Donny Lyle, a Nebraskan prison guard, who had been on the job for a year and had just been promoted, was discovered to be on the lam from interpol for drug and fraud crimes from the Czech republic. The corrections department background check, on the FBI’s national crime database turned up nothing. But when officials subsequently googled Lyle the interpol wanted poster was one of the top results”.
- “Determining the strength of ice is extremely difficult especially for an untrained individual ice must be at least 6 inches thick before it can maintain the weight of a person the temperature must be well below freezing 4 weeks moreover ice is affected by the depth of the water the size of the water body the waters chemistry the distribution of weight on the ice and local climatic factors”
- “From a police report in the North Bay (Ontario) Nugget (Nov. 7): An officer in line at a traffic light, realizing that cars had not moved through two light changes, walked up to the lead car to investigate. The driver said she was not able to move on the green lights because she was still on the phone and thus driving off would be illegal. The officer said a brief lecture improved the woman's understanding of the law.”

APPENDIX B

BRIEFING INSTRUCTIONAL PAMPHLET

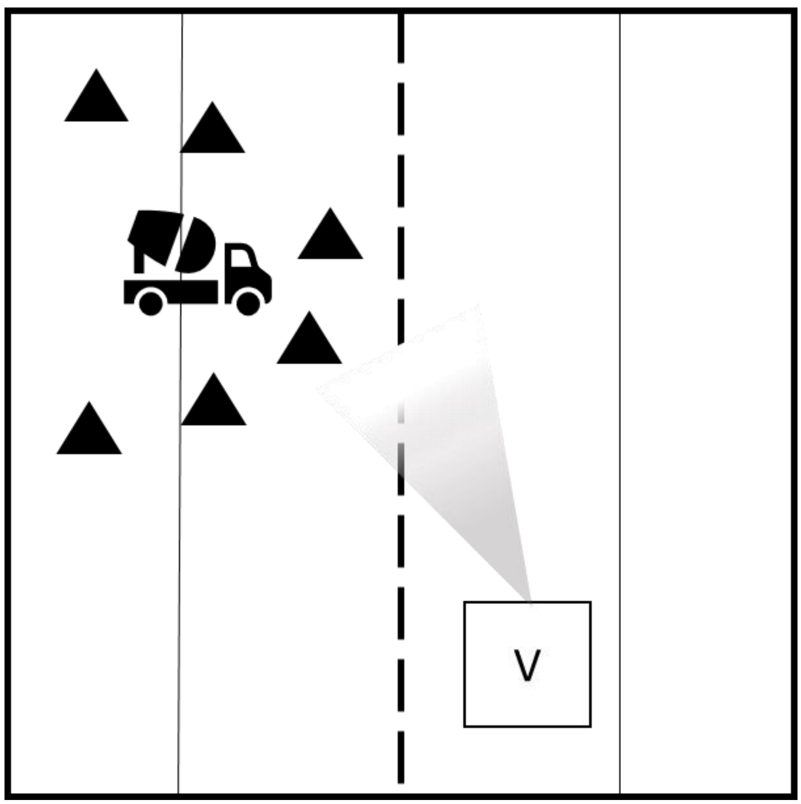
The purpose of this pamphlet is to provide you with instruction on the following topics:

- Latent Hazard Anticipation
    - What it is?
    - Where would it materialize?
    - What information can help me determine a latent hazard may occur?
- Automated Driving Systems (ADS)
    - What is an automated driving system?
    - What procedures will the ADS take-over?
    - What procedures will the ADS not take-over?
    - What is a take-over request?
    - How would I accept a take-over request and successfully take-control of the vehicle?

Please read through this pamphlet carefully and instruct the researcher when you have finished.

Latent Hazard Anticipation

Latent hazards are imminent hazards that have not yet materialized on the roadway. For example, imagine a driver is traveling down a two-way road, where they approach a construction zone blocking the opposite lane. Oncoming traffic is obscured by a large construction vehicle so that the driver cannot see past. In this situation, another vehicle may turn into the drivers' lane to pass the construction zone. The indicator is the construction truck, blocking the view of oncoming traffic. By looking towards the front of the truck as you approach the construction zone, you can look out for the hazard of oncoming traffic.



Partially Automated & Automated Driving Systems

Automated driving systems (ADS) are technologies installed into cars to help perform specific tasks. For example, adaptive cruise control (ACC) allows for the automation to accelerate or brake as the vehicle needs to either avoid crashing into a forward vehicle or maintain current speed. Another example is steering control, where the automation will maintain the vehicle's position within the driving lane. The current ADS has both ACC and steering control, meaning it will accelerate to the appropriate speed as posted by the speed limit signs, and maintain the vehicle's lane positioning.

ADS can perform these actions through built in-sensors that can be obscured by rain, snow, or fog. This means that the automation can fail in certain circumstances, requiring the driver to constantly supervise the automation. In addition, another action the ADS cannot perform is the anticipation of latent hazards.

1a) For drivers in partially automated systems, they must not only supervise the automation but also the forward roadway. One way to consider this is that even though these systems are active, YOU are still driving the vehicle.

1b) For drivers in automated systems, they must supervise the automation. One way to consider this is that when these systems are active, the ADS is driving the vehicle.

If the ADS identifies an issue, it may provide you with a take-over request. A take-over request is a warning submitted by the automation that one or more of its sensors have failed or may fail. In this event, to accept control of the vehicle the driver must ensure their hands are on the steering wheel, feet on the pedals, and they are aware of their surroundings.

APPENDIX C

MOTION SICKNESS SUSCEPTIBILITY QUESTIONNAIRE

This questionnaire is designed to find out how susceptible to motion sickness you are, and what sorts of motion are most effective in causing that sickness. Sickness here means feeling queasy or nauseated or actually vomiting.

Your childhood experience only (before 12 years of age), for each of the following types of transport or entertainment please indicate

1. As a child (before age 12), how often you **felt sick or nauseated** (tick boxes).

	Not Applicable - Never Traveled	Never Felt Sick	Rarely Felt Sick	Sometimes Felt Sick	Frequently Felt Sick
Cars					
Buses or Coaches					
Trains					
Aircraft					
Small Boats					
Ships, e.g. Channel Ferries					
Swings in playgrounds					
Roundabouts in playgrounds					
Big Dippers, Funfair Rides					
	t	0	1	2	3

Your experience over the last 10 years (approximately), for each of the following types of transport or entertainment please indicate

2. **Over the last 10 years,** how often you **felt sick or nauseated** (tick boxes).

	Not Applicable - Never Traveled	Never Felt Sick	Rarely Felt Sick	Sometimes Felt Sick	Frequently Felt Sick
Cars					
Buses or Coaches					
Trains					
Aircraft					
Small Boats					
Ships, e.g. Channel Ferries					
Swings in playgrounds					
Roundabouts in playgrounds					
Big Dippers, Funfair Rides					
	t	0	1	2	3

APPENDIX D

SIMULATOR SICKNESS QUESTIONNAIRE

INFORMATION PROVIDED ON THIS QUESTIONNAIRE IS STRICTLY CONFIDENTIAL.
Your completion of this questionnaire is strictly voluntary and you can skip any questions that you do not want to answer.

Participant ID: __________ Date: ____________

THIS SECTION OF THE QUESTIONNAIRE IS COMPLETED **BEFORE** USING THE DRIVING SIMULATOR.

PRE-EXPOSURE BACKGROUND INFORMATION

1. How long has it been since your last exposure in a simulator? _______ days

   How long has it been since your last flight in an aircraft? _______ days

   How long has it been since your last voyage at sea? _______ days

   How long has it been since your last exposure in a virtual environment? _______ days

2. What other experience have you had recently in a device with unusual motion?

PRE-EXPOSURE PHYSIOLOGICAL STATUS INFORMATION

3. Are you in your usual state of fitness? (Circle one) YES NO

   If not, please indicate the reason:

4. Have you been ill in the past week? (Circle one) YES NO

   If "Yes", please indicate:

   a) The nature of the illness (flu, cold, etc.):

   b) Severity of the illness: Very Mild _________________ Very Severe

   c) Length of illness: _________________ Hours / Days

   d) Major symptoms:

   e) Are you fully recovered? YES NO

5. How much alcohol have you consumed during the past 24 hours?

   ____ 12 oz. cans/bottles of beer ____ ounces wine ____ ounces hard liquor

6. Please indicate all medications you have used in the past 24 hours. If none, check the first line:

   a) NONE _____________

   b) Sedatives or tranquilizers _____________

   c) Aspirin, Tylenol, other analgesics _____________

   d) Antihistamines _____________

e) Decongestants ____________

f) Other (specify): ______________________________

7. a) How many hours of sleep did you get last night? _____ hours

   b) Was this amount sufficient? (Circle one) YES NO

8. Please list any other comments regarding your present physical state which might affect your performance on our test.

____

BASELINE (PRE) EXPOSURE SYMPTOM CHECKLIST

Instructions: Please fill this out BEFORE you go into the virtual environment. Circle how much each symptom below is affecting you right now.

#	Symptom	Severity			
1.	General discomfort	None	Slight	Moderate	Severe
2.	Fatigue	None	Slight	Moderate	Severe
3.	Boredom	None	Slight	Moderate	Severe
4.	Drowsiness	None	Slight	Moderate	Severe
5.	Headache	None	Slight	Moderate	Severe
6.	Eye strain	None	Slight	Moderate	Severe
7.	Difficulty focusing	None	Slight	Moderate	Severe
8a.	Salivation increased	None	Slight	Moderate	Severe
8b.	Salivation decreased	None	Slight	Moderate	Severe
9.	Sweating	None	Slight	Moderate	Severe
10.	Nausea	None	Slight	Moderate	Severe
11.	Difficulty concentrating	None	Slight	Moderate	Severe
12.	Mental depression	None	Slight	Moderate	Severe
13.	"Fullness of the head"	None	Slight	Moderate	Severe
14.	Blurred Vision	None	Slight	Moderate	Severe
15a.	Dizziness with eyes open	None	Slight	Moderate	Severe
15b.	Dizziness with eyes closed	None	Slight	Moderate	Severe
16.	*Vertigo	None	Slight	Moderate	Severe
17.	**Visual flashbacks	None	Slight	Moderate	Severe
18.	Faintness	None	Slight	Moderate	Severe
19.	Aware of breathing	None	Slight	Moderate	Severe
20.	***Stomach awareness	None	Slight	Moderate	Severe
21.	Loss of appetite	None	Slight	Moderate	Severe
22.	Increased appetite	None	Slight	Moderate	Severe
23.	Desire to move bowels	None	Slight	Moderate	Severe
24.	Confusion	None	Slight	Moderate	Severe
25.	Burping	None	Slight	Moderate	Severe
26.	Vomiting	None	Slight	Moderate	Severe
27.	Other				

* Vertigo is experienced as loss of orientation with respect to vertical upright.

** Visual illusion of movement or false sensations of movement, when not in the simulator, car, or aircraft.

*** Stomach awareness is usually used to indicate a feeling of discomfort which is just short of nausea.

THIS SECTION OF THE QUESTIONNAIRE IS COMPLETED **AFTER** USING THE DRIVING SIMULATOR.

POST 00 MINUTES EXPOSURE SYMPTOMS CHECKLIST

Instructions: Circle how much each symptom below is affecting you right now.

#	Symptom	Severity			
1.	General discomfort	None	Slight	Moderate	Severe
2.	Fatigue	None	Slight	Moderate	Severe
3.	Boredom	None	Slight	Moderate	Severe
4.	Drowsiness	None	Slight	Moderate	Severe
5.	Headache	None	Slight	Moderate	Severe
6.	Eye strain	None	Slight	Moderate	Severe
7.	Difficulty focusing	None	Slight	Moderate	Severe
8a.	Salivation increased	None	Slight	Moderate	Severe
8b.	Salivation decreased	None	Slight	Moderate	Severe
9.	Sweating	None	Slight	Moderate	Severe
10.	Nausea	None	Slight	Moderate	Severe
11.	Difficulty concentrating	None	Slight	Moderate	Severe
12.	Mental depression	None	Slight	Moderate	Severe
13.	"Fullness of the head"	None	Slight	Moderate	Severe
14.	Blurred Vision	None	Slight	Moderate	Severe
15a.	Dizziness with eyes open	None	Slight	Moderate	Severe
15b.	Dizziness with eyes closed	None	Slight	Moderate	Severe
16.	*Vertigo	None	Slight	Moderate	Severe
17.	**Visual flashbacks	None	Slight	Moderate	Severe
18.	Faintness	None	Slight	Moderate	Severe
19.	Aware of breathing	None	Slight	Moderate	Severe
20.	***Stomach awareness	None	Slight	Moderate	Severe
21.	Loss of appetite	None	Slight	Moderate	Severe
22.	Increased appetite	None	Slight	Moderate	Severe
23.	Desire to move bowels	None	Slight	Moderate	Severe
24.	Confusion	None	Slight	Moderate	Severe
25.	Burping	None	Slight	Moderate	Severe
26.	Vomiting	None	Slight	Moderate	Severe
27.	Other				

* Vertigo is experienced as loss of orientation with respect to vertical upright.

** Visual illusion of movement or false sensations of movement, when not in the simulator, car or aircraft.

*** Stomach awareness is usually used to indicate a feeling of discomfort which is just short of nausea.

POST-EXPOSURE INFORMATION

1. While in the virtual environment, did you get the feeling of motion (i.e., did you experience a compelling sensation of self motion as though you were actually moving)? *(Circle one)*

   YES NO SOMEWHAT

2. On a scale of 1 (POOR) to 10 (EXCELLENT) rate your performance in the virtual environment: _______

3. a. Did any unusual events occur during your exposure? *(Circle one)* YES NO

APPENDIX E

CALIBRATION QUESTIONNAIRE

- Did you manually drive the vehicle, or did you drive with automated driving support systems?
    - Yes
    - No

If yes, participants will receive this question.

- On a scale of 1 (POOR) to 10 (EXCELLENT) rate your performance in the virtual environment while in the manual driving condition:

POOR									EXCELLENT
1	2	3	4	5	6	7	8	9	10

Driving performance in the virtual environment

Performance anticipating latent hazards

Managing your attention towards the driving task

Attending to and retaining the auditory news stories

If no, participants will receive this question.
On a scale of 1 (POOR) to 10 (EXCELLENT) rate your performance in the virtual environment while in the automated driving condition:

POOR									EXCELLENT
1	2	3	4	5	6	7	8	9	10

Monitoring the automation in the virtual environment

Performance anticipating latent hazards

Managing your attention towards the driving task

Attending to and retaining the auditory news stories

APPENDIX F

DRIVING HISTORY QUESTIONNAIRE

This is a ***strictly confidential*** questionnaire. Only a randomly generated participant ID number, assigned by the research administrator, will be on this questionnaire. No information reported by you here will be traced back to you personally in any way. **You can skip any questions you do not feel comfortable answering.**

Section 1: Demographics

Gender: ☐ Male ☐ Female

Date of Birth: (Month / Day / Year): _______ / _______ / _______ Age: ___________

Race / Ethnicity: ☐ Black / African American ☐ Asian
(check all that apply) ☐ Caucasian ☐ American Indian / Native Alaskan
☐ Hispanic / Latino ☐ Other

Have you participated in a study at this laboratory in the past? ☐ Yes ☐ No

Section 2: Driving History

Approximately how long have you had your driver's license? _______ years _______ months

About how many miles did you drive since your licensure? ____________ miles

Does your license require you to wear glasses or contacts while driving? ☐ Yes, eyeglasses
☐ Yes, contacts ☐ No

Do you have any other restrictions on your driver's license? ☐ Yes ☐ No

If yes, please describe: ____

Are you currently on any over-the-counter or
prescription medications that make it difficult to drive? ☐ Yes ☐ No

If yes, please describe: ____

In the past three months, have you text messaged while driving? ☐ Yes ☐ No

Section 2: Driving History (continued)

Do you think text messaging while driving could affect your driving performance? ☐ Yes ☐ Maybe ☐ No

How frequently do you text message in a day? ☐ Over 20 ☐ 10 - 20 ☐ 5 - 10 ☐ Less than 5 ☐ Never

Within the last three years, have you had any moving violations? ☐ Yes ☐ No

If so, what type and how many? ☐ Speeding How many times? _____
☐ Running red light How many times? _____

☐ Running stop sign How many times? _____
☐ Failure to yield How many times? _____
☐ Other ______________ How many times? _____

Within the last three years, have you been involved in any automobile crashes? ☐ Yes ☐ No

If so, what type of crashes(s)? (Please check all that apply)

☐ Head-on collision (front of car to front of car contact)
☐ Rear-end collision (front of car to rear of car contact)
☐ Side impact or angled collision (front of car to side of car contact)
☐ Sideswipe (door to door contact)
☐ Single car accident (struck tree, sign, pedestrian)
☐ Multiple car accident (more than two cars involved)
☐ Other
☐ I don’t remember

Please describe each of these crashes in a few sentences below.

____
____
____

VITA

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Education

2023	Old Dominion University, Norfolk, VA Ph.D., Psychology - Human Factors, Advisor: Dr. Yusuke Yamani
2019	Old Dominion University, Norfolk, VA M.S., Psychology – Applied Experimental, Advisor: Dr. Yusuke Yamani
2017	Old Dominion University, Norfolk, VA B.S., Psychology

Research Experience

2023 – Present	Research Scientist, Analytical Services & Materials: NASA
2021 - 2023	Research Scientist, National Institute of Aerospace: NASA
2017 – 2023	Researcher, Applied Cognitive Performance Laboratory
2019 – 2019	Research Scientist, Digital Senses Laboratory: VMASC

Teaching Experience

2021 – 2021	Instructor of Record, ODU Department of Psychology
2019 – 2021	Lead Graduate Teaching Assistant, ODU Department of Psychology
2017 – 2019	Graduate Teaching Assistant, ODU Department of Psychology

Selected Publications

Unverricht, J., Chancey, E. T., Politowicz, M. S., Buck, B. K., Geuther, S. & Ballard, K. (2023). Where is the human in the loop? Human Factors analysis of GCSO's conducting live sUAS operations within a remote operations environment. *Proceedings in AIAA SciTech 2023 Forum (p. 2656).*

Unverricht, J. R., Chancey, E. T., Politowicz, M. S., Buck, B. K., & Geuther, S. C. (2023). Eye glance behaviors of ground control station operators in a simulated urban air mobility environment. *Proceedings in 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC)*.

Unverricht, J., Yamani, Y., Chen, J., & Horrey, W. J. (2020). Minding the gap: Effects of an attention maintenance training program on driver calibration. *Human Factors.*

Unverricht, J., Yamani, Y., Horrey, W. J., Chen, J., & Yahoodik, S. (2019). Attention maintenance training: Are young drivers getting better or being more strategic? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 63,* 1991-1995.

Unverricht, J., Samuel, S., & Yamani, Y. (2018). Latent hazard anticipation in young drivers: Review and meta-analysis of training studies. *Transportation Research Record*, 0361198118768530