Human Automation Coordination:

Supporting driver takeover during predictable and unpredictable automation failures

by

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Abstract

Today's vehicles are becoming highly automated, thus changing the driver's task from one of purely driving to one of monitoring the automation. Drivers may fail to monitor the automation, and therefore when drivers are forced to react to unexpected automation failures, they exhibit worse performance than manual driving. Through a driving simulator experiment, this thesis aims to 1) understand how different types of automation failure events, whether predictable (failure events with external cues that a failure may occur) or unpredictable (failure events where there are no cues that a failure may occur) impact the driver's takeover performance, and 2) compare driver takeover performance when using different warning displays, specifically the Takeover Request (TOR; a simple warning that is provided 6s prior to a failure event) and the reliability display (a display that provides drivers with continuous information about the automation's reliability). Findings show that drivers put their hands on the wheel sooner and have greater situation awareness for predictable failure events. Drivers also appear to takeover sooner and have a better takeover quality during predictable failures when the reliability display is present than when TOR is present. As compared to no display, both displays provide a benefit to the driver's takeover performance.

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Chapter 1

1 Introduction

1.1 Motivation for research

Today's vehicles are becoming highly automated. They are capable of detecting and reacting to hazards, and can maintain various levels of vehicle control. The common consensus among vehicle manufacturers is that by increasing the level automation in a vehicle, they will also increase the vehicle's safety, as 94% of crashes are due to human error (Singh, 2015). However, the automated vehicles currently on the market are not fully automated, and require the driver to monitor the environment and the vehicle's performance. If the vehicle encounters a situation it cannot handle, the driver must takeover control. Therefore, when the automation is on, the role of the driver changes from one where the driver is in control of the vehicle's dynamics, to one where the driver must be a monitor of the automation's behavior.

The effect of changing a human's task from one of direct control to one of supervision has been widely studied, and has been shown to have negative consequences such as: the out-of-the-loop performance problem, loss of situation awareness, over-trust and complacency (see, e.g., Bainbridge, 1983; Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Endsley & Kiris, 1995; Parasuraman, Molloy, & Singh, 1993). In order to combat such issues in the aviation industry, protocols were created and pilots were trained on how to safely use autopilot. However, in the automotive industry drivers are usually not trained on how to use the vehicles' automation. While drivers may learn how to operate the automated systems using the owner's manual, 7 out of 10 drivers are not aware of the manufacturers' warnings about the automated system's limitations (Jenness, Lerner, Mazor, Osberg, & Tefft, 2008). Additionally, according to the work of Beggiato and Krems (2013), half of drivers who use adaptive cruise control (ACC) systems have not read the owner's manual, and most drivers who use ACC systems are not aware of the system limitations. Anecdotal evidence from the personal interviews that the author of this thesis has conducted with drivers who use ACC systems suggest that often times, drivers learn the limits of their ACC system when they experience them. For example, one driver told the author that when getting on the highway off ramp after driving in dense Los Angeles traffic, the ACC would cause his car to speed up significantly, almost causing a crash. After becoming aware of this automation limit, the driver was able to safely takeover control of the vehicle.

Tesla has recently come under fire for issues concerning proper driver use of their automated systems, which they call AutoPilot. Tesla states that they do warn drivers to monitor the road and remain vigilant as AutoPilot cannot handle every situation it encounters. The system also requires drivers to regularly put their hands on the wheel throughout the AutoPilot drive as an indication that they are paying attention. However, recent fatal crashes involving Tesla vehicles indicate that these warnings and methods may be insufficient to keep the driver in the loop.

On May 7, 2016, a Tesla Model S with AutoPilot engaged collided with a semitrailer that was making a left turn. According to the report produced by the National Transportation Safety Board (NTSB), the driver of the Tesla had 10 seconds of clear visibility to observe and respond to the semitrailer, but neither the automation nor the driver took any measures to avoid a collision (National Transportation Safety Board, 2017). The report concluded that while the automation functioned within its design specifications, the driver appeared not to comprehend the limits of the automation's abilities, over-relied upon the automation, and allowed himself to be distracted from the driving/monitoring task. The report also concluded that monitoring regular driver engagement by requiring drivers to put their hands on the steering wheel is an insufficient method to assess driver engagement, as driving is a visual task.

Two additional fatal collisions occurred in the United States in 2018—one on March 23, 2018 in California involving a Tesla Model X with the AutoPilot engaged, and one on March 18, 2018 in Arizona involving an Uber Technologies Inc. automated test vehicle. While the preliminary NTSB reports do not specify any causation for these crashes, the reports do appear to indicate that the drivers were not fully engaged in the driving task prior to the collisions. Regarding the Tesla crash, it is likely that the driver was not aware of a possible incident as he performed no evasive maneuvers prior to the crash (National Transportation Safety Board, 2018a). Photos of the crash showed that the lane markings for one side of the "V" that marks the edge of the exit/entrance lanes was faded, likely causing the vehicle's automation to follow the visible lane marking, and thus hit the damaged crash attenuator. Given the information gleaned from these photos, other Tesla drivers have attempted to replicate this possible system boundary issue. Videos that these drivers have posted on YouTube show that they were able to successfully replicate this system boundary issue. As the drivers were aware of the possible issue with the automation, each driver successfully took over control from the automation. For the Uber collision, the operator glanced down from the road several times before the collision to monitor the vehicle's self-driving interface, and only intervened to mitigate the collision less than one second prior to impact. This collision involved a woman crossing the street into the path of the Uber vehicle. While the woman crossing the street was not very visible (she was clothed in black and did not have any side reflectors), the vehicle's radar and LIDAR systems registered an unknown object on the road 6 seconds prior to impact, and did not alert the operator as that was outside of the test vehicle's design specifications (National Transportation Safety Board, 2018b).

The combination of the information obtained so far from these fatal collisions indicates that there are issues with the current design of automated vehicles. In order to improve the design of these vehicles in the future, it is important to understand how drivers interact with automated vehicles, and then design additional systems to facilitate the driver's use of the automation, and eventually improve vehicle safety.

1.2 Thesis Overview

The focus of this thesis is on understanding how drivers interact with automated vehicles, and analyze different systems that are in place, or are being proposed, which are meant to facilitate the driver's use of automation.

Research has shown that in the presence of automation, drivers can become reliant on the automation and may fail to monitor the driving environment or understand the limitations of the automation. These issues may impact the driver's situation awareness, and may be exacerbated by changes in the driver's trust in automation and workload. As compared to manual (or non-automated) driving, drivers of automated vehicles also engage in non-driving related tasks (i.e. secondary tasks, which are tasks that are secondary to the primary driving task) significantly more often, which lead to distraction (de Winter, Happee, Martens, & Stanton, 2014). Engagement in secondary tasks would degrade the driver's situation awareness, and thus impact the driver's ability to safely takeover control of the vehicle at unexpected failures. In order to further understand the impact of automated driving on driver performance, a literature review was conducted (see Chapter 2).

In the context of this thesis, unexpected failure events are unscheduled events where the automation either turns off, or acts in an unforeseen manner, thereby requiring the driver to regain manual control from the automation. These unexpected failure events may occur at the limits of the automation's capabilities, or they may occur due to an algorithmic error. While these events are called unexpected failures, they may not necessarily be automation failures (as the automation may not have been designed to handle the relevant situation); however, from the perspective of the driver whose mental model may not include the automation's behavior at its limits, they can be considered to be failures.

Since driver's takeover performance may not always be sufficient during unexpected failures, researchers have started to identify different methods to positively impact the driver's takeover performance. In this literature review, four different factors that have an impact on the driver's takeover performance were identified and explored in section 2.3: 1) anticipating failures, 2) Takeover Requests (TORs), 3) reliability displays, and 4) training. The exploration of the literature for these four factors revealed several research gaps. Two of these gaps, detailed below under two objectives, were selected for further study in this thesis.

Objective 1: To assess how driver takeover performance is impacted by different failure events, in particular, predictable and unpredictable failure events.

There are two different types of unexpected failures that can occur: predictable and unpredictable failures (see section 2.3.1). Predictable failure events are ones where the driver has external indicators that a failure event may occur, while unpredictable failure events have no indicator that a failure may occur. In the study of takeover performance, the literature does not make a systematic distinction between these different types although it is reasonable to expect that takeover performance may be different across these two different failure types. Therefore, the first objective of this research is to compare whether drivers experience a different takeover performance at predictable and unpredictable failure events.

Objective 2: To understand how driver takeover performance during predictable and unpredictable failure events is impacted by different displays, in particular, the Takeover Request (TOR) and the reliability displays.

With increased automated driving, drivers interact with secondary tasks significantly more often than they do during manual driving (e.g. Carsten, Lai, Barnard, Jamson, & Merat, 2012). This can cause drivers to decrease their monitoring of the driving environment, and hinders the driver's situation awareness. In order to warn drivers of an impending takeover, researchers have developed Takeover Requests (TORs), alerts provided to the driver a few seconds before a failure event. However, those displays may not help drivers manage their attentional states throughout the drive, and may promote driver disengagement until the TOR appears, thus decreasing the driver's situation awareness. Therefore, researchers have also looked into the use of reliability displays that continually provide drivers with information about the state of the automation's reliability. While each display type has shown benefits regarding the driver's takeover performance, researchers have yet to compare the benefits of these different displays (see section 2.3.2 and 2.3.3) in general, and for predictable and unpredictable failures in particular.

In order to address these objectives, a driving simulator study was conducted. The experimental methods are presented in Chapter 3, the experimental measures in Chapter 4, the data analysis methods in Chapter 5, and the results in Chapter 6. Chapter 7 summarizes and discusses the results, while Chapter 8 presents the contributions to the field.

Chapter 2

2 Literature Review

2.1 Automation in Vehicles

Vehicle automation ranges from low levels, such as GPS navigation and Forward Collision Warning (FCW), to mid-levels where the car can control its lateral and longitudinal motion, to even higher levels where the car is able to detect and react to hazards on its own. Given the wide range of capabilities in the automation available in cars, the Society of Automotive Engineers (SAE) created a classification system that categorizes the different levels of automation in vehicles and specifies the level of driver involvement that may be required. The scale identifies six different levels of automation for driving, and it ranges from no automation to full automation (Figure 1). This scale also identifies the amount of driver input that is required for each level of automated driving. As seen in Figure 1, until the vehicles are at the SAE level 5 automation, a transition of control from the automation to the driver may still be required as the vehicles may not be able to handle an impending driving situation. This means the driver is the fallback for the automation if there is an unexpected failure, or if the automation is aware that it will soon reach its limits. Therefore, until drivers are in SAE level 5 automated vehicles, drivers must continue to monitor the environment, and remain alert and vigilant for a possible intervention.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 1: Levels of automated driving from SAE International report J3016. (SAE International, 2014). The line depicted in blue separates where the driver has control of the car and where the automation has control of the car.

2.1.1 Current state of vehicle automation

Currently, there are two different directions that companies are going with their automated vehicles. One set of companies, such as Uber and Waymo, are focusing more on creating a fully automated fleet of vehicles which will be tested in different locations prior to release for public use. Another set of companies— specifically mainstream car manufacturers like Tesla, Volvo, etc.—are continually increasing the level of automation available in their cars with each new release. While there are two different directions that these companies are going, the focus of this thesis is on the automated vehicles that are currently available to consumers.

Many of the new vehicles that are being released into the mass market are equipped with Advanced Driver Assistance Systems (ADAS), which can include Forward Collision Warning (FCW), Adaptive Cruise Control (ACC), Lane Keeping (LK, also known as Assistive Steering [AS], or Adaptive Lane Following [ALF]), Lane Departure Warning (LDW), and Traffic Jam Assist (TJA), as well as other additional automated functions. The combination of all the aforementioned automated systems brings the level of vehicle automation to a level 2 or level 3 depending on the vehicle.

Even though the human factors implications of these level 2 and level 3 automated vehicles are still being researched, it is already clear that current ADAS systems have limits due to sensor limitations and data processing (Larsson, 2012). Today, most of the ADAS systems rely on radar and computer vision technology to determine the location of other cars on the road, determine the location of obstacles, and determine where the car should be placed in the road. As level 2 and level 3 automation rely heavily upon ACC and LK systems to achieve the partial and conditional automation that is discussed in Figure 1, these two systems will be focused on significantly more in this thesis. Additionally, as many car companies are integrating warning systems into their automated vehicles, those will also be focused on in this thesis.

A brief overview of these systems are presented below, along with possible failure situations that drivers may experience using these systems.

Adaptive Cruise Control (ACC)

ACC is a technology that functions in a manner that is very similar to cruise control. It can maintain a speed set by the driver, but it has the added benefit of being able to maintain a headway gap between the ego-vehicle and the lead vehicle (Yadav & Szpytko, 2017). In the event the gap between the two cars decreases, the ACC will slow down the ego-vehicle to maintain that gap. In order to sense the location of the lead vehicle, modern vehicles are equipped with radar systems which send out signals that are then reflected back. This technology, however, is limited in several ways. The first manner is that there is a limit for the distance at which their signals can reflect back. Additionally, research has shown that many ACC systems have issues with identifying "cut-in" situations, which means that the ACC may speed up, rather than slow down when a new vehicle cuts in front of the ego-vehicle. The ego-vehicle will continue to speed up until it identifies the cut-in vehicle as the new lead vehicle, or until the driver turns off the ACC (Larsson, Kircher, & Andersson Hultgren, 2014). Another issue with the ACC systems is that they are not always capable of detecting static objects (Nilsson, 1996), which presents issues when traffic suddenly comes to a standstill on the highway, or when there is a vehicle that is stopped on the road. The ACC also is limited in its ability to detect the lead vehicle on curvy roads. Additionally, according to ownership manuals, the ACC is not designed to handle critical traffic situations such as city driving or heavy traffic, and is also not meant to be operated on highway on/off ramps (e.g., "Tesla Model S Owner's Manual," 2018).

Lane Keeping (LK)

LK is another technology that is being implemented in many state-of-the-art vehicles. LK functions by maintaining control of the vehicle's steering. LK technology often uses video sensors and computer vision technology to function. Therefore, in order to function properly, the lanes must be clearly visible, and not adjusted by construction, or poor weather conditions. Depending on the car manufacturer, another limit that may be placed on the LK technology in cars is the amount of torque that the LK system can apply on steering. This may inhibit the LK system from handling roads with a high curvature.

Warning Systems

Given the limitations of the ACC and lane keeping systems, and the fact that the NSTB reports show that drivers regularly end up out of the loop when these automated systems are on, car manufacturers have attempted to mitigate these issues by checking that the drivers are in the loop and by bringing drivers back into the loop. In order to make sure that drivers are not out of the loop, Tesla uses a system that requires the driver to regularly put their hands on the wheel for the automation to remain active. If the driver does not put their hands on the wheel regularly, the system will flash a white warning on the top of the dashboard, and the system may issue a chime. If the driver still does not place their hands, the warning will appear again with a chime, until the driver places their hands on the wheel. If the driver persists to not place their hands on the wheel, eventually Tesla's automation will sound a continuous chime and slow the vehicle to a complete stop ("Tesla Model S Owner's Manual," 2018). While Tesla states that this manner is effective, the driver referenced in the NSTB's 2017 report repeatedly was issued this warning, and still was not paying attention to the road ahead. In addition to its "Hands-On-Wheel" chime, the Tesla Model S also includes a warning that tells the driver to "Take Over Immediately", and drivers are required to takeover steering of the vehicle as soon as that warning appears on their dashboard, with a chime ("Tesla Model S Owner's Manual," 2018). As of yet, Tesla has not commented about the effectiveness of this warning.

Given the possibility of critical and fatal situations in automated driving, it is necessary to understand what makes a driver go out of the loop when the automation is engaged, and how to both keep the driver in the loop and get the driver back into the loop. This understanding of warning systems and takeover requests is a major focus of this thesis and is discussed in section 2.3.2.

2.2 Impact of automation on drivers

Car manufacturers are adding automation capabilities to vehicles with the intent of eventually reaching a fully automated car, where the human is completely removed from the driving tasks. However, mainstream automobile companies are introducing the automation in a piecemeal approach, and are requiring humans to monitor the system in case of an automation failure, as the automation available is currently at SAE Level 2 and Level 3. While the addition of partial automation does relieve the driver from actively controlling the vehicle's dynamics (to the point that drivers can actively partake in tasks secondary to the primary driving task), research has shown that if a driver is required to respond to unexpected failures by taking over control from the automation, their reaction time is slower and the quality of their driving performance is poorer than when drivers are required to respond to the same situations (such as a vehicle stopped in the ego-lane) during manual driving (Merat & Jamson, 2009; Merat, Jamson, Lai, & Carsten, 2012; Merat, Jamson, Lai, Daly, & Carsten, 2014; Rudin-Brown & Parker, 2004; Shen & Neyens, 2017; Stanton, Young, & McCaulder, 1997). Moreover, the addition of automation can increase the driver's crash risk relative to manual driving (Stanton et al., 1997). Research has also shown that when the level of automation is increased from purely longitudinal automation (adaptive cruise control), to also including the lateral automation (lane keeping), the driver's takeover performance is further degraded (Carsten et al., 2012; Strand, Nilsson, Karlsson, & Nilsson, 2014).

In order to try to ameliorate the issue of longer reaction time and poorer driving performance when responding to unexpected failures, researchers have first attempted to understand the human factors implications of automated driving. Research shows that the addition of automation to driving impacts takeover performance due to automation influencing drivers in the following areas: 1) monitoring, 2) situation awareness, 3) trust, and 4) workload. The sections below discuss these factors separately, although it should be noted that they are interrelated, and have an impact on each other.

2.2.1 Monitoring

When automation is added to a system, it changes the operator's task. The operator's task changes from one of manual control to monitoring a system for possible control takeover in case of a system failure (Bainbridge, 1983). As driving is primarily a visual task, if a driver is not monitoring the road environment, it is not possible to prepare for a situation that may arise. In fact, when a driver's monitoring degrades, reaction time to a request or required transfer of control increases (Merat et al., 2012).

When examining the driver's gaze behavior to understand how the driver's manner of monitoring changes when vehicle control automation is introduced or is increased from longitudinal to longitudinal and lateral control, research showed that the driver's visual attention to the road decreased (Carsten et al., 2012; de Winter et al., 2014), their gaze fixations were more erratic (Louw, Madigan, Carsten, & Merat, 2017), and drivers had more look-ahead fixations with horizontal dispersions (Navarro, François, & Mars, 2016) as compared to manual driving. This change in the manner of the driver's monitoring is likely due to the monotonous nature of monitoring automation, and the subsequent decrease in the driver's vigilance (Beggiato et al., 2015). Due to this monotony, when automation is added to a system, or the level of automation is increased, drivers show an increase in their level of engagement with secondary tasks than on the primary monitoring task (Carsten et al., 2012; Jamson, Merat, Carsten, & Lai, 2013; Llaneras, Salinger, & Green, 2013; Naujoks, Purucker, & Neukum, 2016). Increased engagement in secondary tasks causes the driver to respond slower to lane departure events (Shen & Neyens, 2017), decreases the driver's monitoring of the driving environment and event detection, deteriorates the driver's situation awareness (de Winter et al., 2014), and inhibits the driver's ability to construct a good mental model of the road which makes it take longer for drivers to cognitively reorient themselves to the road (Zeeb, Buchner, & Schrauf, 2015).

In order to improve the driver's monitoring of the driving environment, research has shown that it is beneficial to develop displays that will encourage drivers to gaze towards the road center during high levels of automation. This is likely to increase the driver's situation awareness during high levels of automation (Louw & Merat, 2017), and thus to help the drivers takeover control of the vehicle should a takeover situation arise.

2.2.2 Situation Awareness

Situation awareness has three levels: perception, comprehension and projection (Endsley, 1995).The degradation of monitoring described above can impair perception and thus comprehension and projection, and lead to a decrease of situation awareness in all levels (Stanton & Young, 2005). The reduction in a driver's situation awareness can impact the driver's ability to make decisions and maneuver the car at critical situations and has been associated with delayed braking responses (Young & Stanton, 2007). Conversely, an increase in the driver's situation awareness positively influences the driver's ability to regain control of the car during critical situations (van den Beukel & van der Voort, 2013).

However, a driver's situation awareness during automated driving is also dependent upon the driver's cognitive load and available mental resources (Ma & Kaber, 2005). In fact, Ma and Kaber (2005) showed that drivers who are having a conversation on a hand-held cell phone while using the ACC have a lower situation awareness relative to drivers who are using the ACC without a secondary task. Performance of other secondary tasks while driving with automation, such as visual or manual or visual-manual secondary tasks, also decreases the driver's situation awareness, as when drivers who are engaged in the task must visually and cognitively re-orient themselves back to the road when an issue comes up; this causes the driver to take a longer time to understand the problem, and leads to a diminished takeover quality (Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Zeeb et al., 2015; Zeeb, Buchner, & Schrauf, 2016).

While the cognitive load of a secondary task decreases the driver's situation awareness, a driver's situation awareness can increase when the situation that they are driving through becomes more complex.

Research has shown drivers engage less in secondary tasks during high traffic situations (Beggiato et al., 2015). As a driver's engagement in secondary tasks is directly related to their situation awareness (Schömig & Metz, 2013), in complex driving situations, drivers may decrease their engagement in secondary tasks to improve their situation awareness.

Yet, issues about driver's situation awareness are not solely caused by the driver—they are also caused by the inherent design of the automation, and its lack of transparency in its performance. Drivers can be unaware of the limits of the automation or why it may be acting in a specific manner, especially in safety critical failure situations. Understanding why the automation is at its limit, or why it is failing is paramount, because, according to the definition of situation awareness, the driver must also comprehend and project what is occurring in the environment (Endsley, 1995). Due to this lack of transparency, drivers are likely to take a significantly longer time to determine what is occurring with the system and why a system failure is occurring (Bainbridge, 1983).

2.2.3 Trust

Trust is a predictor of automation use (Parasuraman & Riley, 1997), and therefore has a significant impact on how much the operator monitors the system, and how the operator uses the automated system. When operators trust a system more, they end up monitoring the system significantly less (Lee & See, 2004; Muir & Moray, 1996). Additionally, when operators have a higher complacency with the automated system, they re-allocate their attention from safety tasks to non-safety tasks (i.e. secondary tasks in the driving domain), which therefore decreases their situation awareness of the environment (Parasuraman & Manzey, 2010; Parasuraman et al., 1993; Parasuraman & Riley, 1997).

The relationship depicting the inverse relationship between trust and monitoring has been demonstrated several times in the realm of automated vehicle research using glance data: with increased trust, drivers glance towards a secondary task significantly more often (Beggiato et al., 2015; Hergeth, Lorenz, Vilimek, & Krems, 2016; Korber, Schneider, & Zimmermann, 2015). In addition to issues with glance behavior, research has shown that drivers of highly automated vehicles respond significantly later to events when they over-trust the automation (Payre, Cestac, & Delhomme, 2016).

Trust, however, is dynamic and evolves through system use. Muir and Moray (1996) showed that when operators initially distrusted a system, long term use of the automation helped the operator build trust. In the context of automated driving, researchers have shown that participants increase their trust in the automation over the course of a 20 minute drive with safety critical situations (Gold, Körber, Hohenberger, Lechner, & Bengler, 2015). The driver's trust likely increased as the automation functioned according to the driver's expectations. The initial trust in automation can also be impacted by the information presented to the participant prior to the experiment, and has been shown to impact their reliance upon the automation, and ability to takeover in critical situations (Körber, Baseler, & Bengler, 2017). As long as the information presented to participants prior to the experiment presents an accurate portrayal of the automation's capabilities and limitations (i.e. the failures the driver experiences in a scenario are already known prior to the drive), the driver's will show an increase in trust in the system, and automation failures will not negatively affect the driver's trust in the automation (Beggiato & Krems, 2013). This research therefore shows that as driver's trust is dynamic, it can be calibrated such that drivers have an appropriate level of automation trust, and form a correct mental model of how the automation functions. This ultimately will influence the driver's reliance upon the automation.

2.2.4 Workload

One of benefits of semi-automated, and highly automated driving is that a driver's workload is significantly reduced (Stanton et al., 1997) as they are relieved from lateral and/or longitudinal control of the vehicle. In fact, there is a direct correlation between the driver's workload and the level of automation—when the level of automation increases, the driver's perceived workload decreases (de Winter et al., 2014). While at the outset it may seem beneficial to decrease workload, research has shown that when drivers use ACC, they have more difficulty in taking over control of the vehicle during failure situations (de Waard, van der Hulst, Hoedemaeker, & Brookhuis, 1999; Stanton et al., 1997). This may be because drivers overly rely on the automation, which therefore decreases their situation awareness. Other researchers have shown that when workload decreases with the increase of the level of the vehicle's automation, drivers experience a deterioration in their situation awareness and interact with secondary tasks significantly more, which shows that drivers monitor the environment and the automation significantly less (de Winter et al., 2014).

2.3 What impacts a driver's takeover quality?

As discussed earlier, at unexpected failure events, drivers can exhibit a poor takeover quality and reaction time. Researchers have therefore attempted to look into how to improve takeover time and quality by addressing the following areas of research: 1) the impact of anticipatory information (i.e. information from the driving environment that the driver can use to anticipate a failure event) on a driver's takeover quality, 2) the impact of adding take-over requests (TORs) to get the driver back into the loop, 3) the impact of reliability displays to keep the driver in the loop, and 4) the impact of training on driver's takeover quality and ability to stay in the loop.

2.3.1 Anticipating Failures

Thus far, researchers have examined driver reaction time and takeover performance to a variety of unexpected failure types, such as an object on the road, or induced vehicle drift, etc. However, there is a lack of systematic research investigating the differences between the impact of different types of failure events on takeover quality. The different failure events that have been explored in research thus far have been compiled in Table 1.

An analysis of the different failures that were explored show that the unexpected failures that have been used in research break down into two different failure types: predictable and unpredictable failures. A predictable failure is one where the driver, based on their knowledge of the automated system, looks at the road and sees that there is a situation that the automation would not be able to handle (i.e. there are indicators that a driver can notice to anticipate the unexpected failure event). An example of a predictable failure could be bad weather, a stationary car in the ego-lane, or an upcoming intersection. An unpredictable failure is one where the driver would not expect the system to act incorrectly; from the driver's perspective, the automation fails without a good reason, possibly due to sensors, algorithms, etc. (i.e. there are no indicators that a driver can use to anticipate the unexpected failure event). An example of an unpredictable failure could be when the automation unexpectedly accelerates or fails to brake.

Table 1: Different failure types that have been used in research

Failure Type	Failure Event	Citation
Predictable	Obstacle avoidance in lane or ego-lane is blocked, or collision suddenly occurs blocking the ego-lane	(Gold, Damböck, Lorenz, & Bengler, 2013; Hergeth, Lorenz, & Krems, 2017a; Navarro et al., 2016; Zeeb et al., 2016)
	Person, animal or item suddenly walking into lane	(Gold, Damböck, Bengler, & Lorenz, 2013; de Winter, Stanton, Price, & Mistry, 2016)
	Poor road visibility due to weather	(Helldin, Falkman, Riveiro, & Davidsson, 2013)
	Lane markings end, lane markings are faded, a lane change is required, or high road curvature	(Naujoks, Mai, & Neukum, 2014; Naujoks et al., 2017; Zeeb et al., 2016b)
	Stranded vehicle in the ego-lane	(Gold et al., 2015)
	Automation turns off at intersections	(de Winter et al., 2016)
	Construction site with a change of lane markings on the road	(Melcher, Rauh, Diederichs, Widlroither, & Bauer, 2015)
Unpredictable	ACC does not decelerate properly	(Strand et al., 2014)
	Automation incorrectly responding to the	(Beller, Heesen, & Vollrath, 2013)

	lead vehicle by incorrectly braking	
	Lead vehicle cut-in event[1] causes the vehicle to suddenly accelerate until the ACC recognizes the lead vehicle	(Larsson et al., 2014)
	Automation suddenly turns off (based on variable eye movement)	(Merat et al., 2014)
	Induced drift that made the car go out of the lane	(Shen & Neyens, 2014, 2017)
	ACC failed to detect lead vehicle	(Stanton et al., 1997)

While there has been a lack of systematic research on the differences between the impact of predictable and unpredictable failure events on driver takeover performance, the research community is beginning to study the impact of anticipatory information on a driver's monitoring strategy and takeover performance. In the context of automated driving, anticipatory information is the information that a driver can glean by monitoring the driving environment (which includes the road and any display within the car, such as the speedometer) combined with the driver's knowledge of the automation to help them anticipate a potential takeover situation, and ensure a safe transfer of control. Thus far, most of the research has focused on the impact of traffic density on a driver's monitoring and takeover performance. This is because heavy traffic is an ACC system limit (the ACC can generally function above a certain speed), and as heavy traffic causes unexpected failures and critical situations to become more hazardous. This body of literature shows that in heavy traffic drivers of highly automated vehicles tend to focus more of their visual attention to the roadway than a secondary task (Beggiato et al., 2015; Jamson et al., 2013), likely improving their situation awareness. However, the aforementioned improvements in driver monitoring does not appear to impact the driver's takeover performance, as drivers have significantly longer takeover times during increased traffic (Gold, Körber, Lechner, & Bengler, 2016). Gold et al. (2016) argued that the increase in driver takeover time is due to drivers attempting to gain situation awareness to determine how to maneuver and avoid the critical situation. As there may not be a benefit of increased driver monitoring on takeover time and quality during heavy traffic situations, researchers have subsequently looked into the impact of other anticipatory information that drivers may observe while driving, such as the vehicle's speed as an indicator of a system limit (Dogan et al., 2017), road signs as an indicator of speed limit, road conditions and upcoming hazards (Beggiato et al., 2015), and lane marking conditions as an indicator of lane keeping limits (Naujoks et al., 2017).

[1]A lead vehicle cut-in event is defined as an unpredictable failure because drivers expect the ACC to always recognize cars in front of the ego-vehicle. One example of this event is when a car changes lanes and becomes the new lead vehicle for the ACC system. Sometimes, the ACC is not able to immediately recognize this new lead vehicle and, depending on the ACC set speed, may accelerate until it recognizes the new lead vehicle.

While performing research on the impact of decreasing traffic density on a driver's use of Traffic Jam Assist (TJA), Dogan et al. (2017) also looked into the impact of anticipatory information on driver monitoring and takeover performance. As drivers were informed that the TJA was operational at speeds less than 50 km/h, and therefore only operational in high traffic situations, Dogan et al. (2017) compared driver monitoring and performance when the TJA suddenly turned off (i.e. no anticipatory information), to when the TJA turned off after the vehicle's speed increased to 50 km/h and the traffic density decreased (i.e. anticipatory information). Their work showed that when drivers were provided with anticipatory information, drivers monitored the driving environment more than when there was no anticipatory information. However, the drivers did not monitor the decrease in traffic density, rather, they monitored the vehicle's speed increasing to 50 km/h on the dashboard. This increase in speedometer monitoring rather than traffic density is likely due to the subjective nature of the definition of high traffic, and the lack of discrete and clear differences in the traffic density moment to moment, as compared to the clear system boundary of 50 km/h. Therefore, this likely shows that when drivers are knowledgeable about the automation's limits, they will monitor the salient information that will inform them of an impending unexpected failure. Unfortunately, as drivers had to look down towards the dashboard to monitor the speed, there was no improvement in driver performance at the takeover event.

As road signs can also provide drivers with anticipatory information by informing them of upcoming road conditions, such as construction zones, Beggiato et al. (2015) attempted to see if drivers of automated vehicles perceive road signs. Their work showed that as drivers spent nearly 75% of their time during highly automated driving looking at the secondary task that was provided to them, they did not perceive the road signs. Therefore, in order for a driver of a highly automated vehicle to react to road signs as anticipatory information, they must be cued into their potential importance prior to or during driving.

Drivers can also monitor visual indicators of the lateral control limits of automation, such as the lane markings changing due to construction. Naujoks et al. (2017) looked at how drivers perform at the limits of lateral automation in partially automated driving. The limits that these researchers used were 1) lane markings ending, 2) a required lane change due to temporary lane markings, and 3) the road suddenly having a high curvature. A visual-auditory TOR was issued as soon as the drivers reached the limit of the automation. While drivers were able to takeover at each of these system limits, most drivers were not able to explain why the TOR was issued. Given that the limits of the lateral automation were not introduced to participants at the beginning of the experiment, participants may not have been aware of any of these changes in the road, thereby impacting their recognition of why the TOR was issued.

The body of literature cited above shows that if drivers are aware of the anticipatory information in the driving environment, drivers may change their monitoring strategy, which may impact their takeover quality.

2.3.2 Take-Over Request (TOR)

As mentioned earlier, drivers respond poorly to failure events that are unexpected (Nilsson, Strand, Falcone, & Vinter, 2013; Rudin-Brown & Parker, 2004; Stanton et al., 1997; Strand et al., 2014). Therefore, in order to avoid these potentially dangerous situations, research has shown that it is necessary to make drivers aware of an impending transition of control early (Damböck, Bengler, Farid, & Tönert, 2012). In fact, drivers react significantly faster to expected events than unexpected events (Ruscio, Ciceri, & Biassoni, 2015). Therefore, the idea of a TOR was developed in order to warn drivers of impending takeover situations. A TOR is similar to a warning signal, and is a tool that is used to warn drivers of an impending issue with the automation by informing them that they need to resume control of the vehicle. When the TOR was first introduced to drivers using the ACC in a research setting, drivers were able to effectively resume control of the vehicle even if they were distracted (Lee, McGehee, Brown, & Marshall, 2006). Naujoks & Neukum (2014) showed that alerting the drivers even 2s prior to a failure event allowed drivers to decrease the amount of braking required to avoid the critical situation, and also increased the driver's Time to Collision (TTC)[2], thus decreasing the situation criticality.

Subsequent to determining that it was beneficial to alert drivers to an impending transition of control, most research on the use of TORs has focused on trying to determine the optimal TOR lead time (i.e. the time between the TOR and the failure event) that would prompt drivers to both react quickly and have a smooth takeover quality. A literature review performed by Eriksson and Stanton (2017b) showed that the TOR lead times used in research ranged between 0s and 30s, with a mean of 6.37 ± 5.36s. Among the literature that was reviewed, the reaction time to the TORs ranged from 2 to 3.5s. However, while the reaction time was fairly consistent among the research that was reviewed, drivers with a shorter TOR lead time respond more quickly than drivers with a longer TOR lead time (Gold, Damböck, Lorenz, et al., 2013). Additionally, the length of the lead time has a significant effect on the driver's takeover quality, with shorter TOR lead times causing drivers to have a poorer takeover quality (Gold, Damböck, Lorenz, et al., 2013).

In addition to determining the optimal TOR lead time, other research has focused on the optimal TOR alert modality to prompt the fastest driver reaction time. Three types of modalities have been explored:

[2] The TTC is defined as the time required for the ego-vehicle to collide with the critical situation if the ego-vehicle continued driving at the same velocity.

Visual, Auditory and Tactile. Alerts implemented with a tactile vibration proved to lead to the fastest reaction times relative to auditory or visual TORs (Scott & Gray, 2008). However, the combination of the visual and auditory alert modalities led to a faster reaction time than the tactile modality alone (Lee et al., 2006). Naujoks, Mai, and Neukum (2014) showed that combining the visual and auditory alert modalities made drivers react more quickly than by solely providing them with a visual alert, as it gave drivers an added sense of urgency to the situation. Additionally, with the visual and auditory alerts, drivers maintained better lane keeping when the TOR was issued.

While TORs are beneficial in getting drivers back into the loop, they do have some issues. As drivers may not have been attentively monitoring the vehicle or their surroundings prior to the alert, they may find the alert surprising or startling, which may impact their takeover quality. Furthermore, when alerted, it takes time for the drivers to cognitively reorient themselves to the roadway after being engrossed in a secondary task (Zeeb et al., 2015), which would negatively impact the driver's takeover quality depending on the criticality of the situation, and the amount of time that the drivers have to takeover control.

When the TOR is added to a system, drivers tend to have increased trust in the automated system (Gold et al., 2015). Over time, this increased trust may prove to be detrimental to the drivers as they may over-rely on the automation, and on the appearance of a TOR prior to a failure situation (Parasuraman & Manzey, 2010). This presents issues when a failure situation arises and no TOR appears. Furthermore, even when a TOR appears, drivers may not understand why the TOR appeared (Naujoks et al., 2017), which may make it take longer for the drivers to figure out how to maneuver (Beggiato et al., 2015).

2.3.3 Reliability Displays and Displaying Vehicle Limits

Given the limits of TORs, and the fact that research has shown that when drivers have insufficient knowledge of the limitations of automation, they have inappropriate levels of trust in the automated system (Stanton et al., 1997), researchers have developed reliability displays and other informational displays, with the aim of providing drivers of automated vehicles with more transparency, and helping drivers properly calibrate their trust to the abilities of the automated cars (Hoff & Bashir, 2015).

In order to determine the informational needs of drivers of automated vehicles, Beggiato et al. (2015) performed a study that showed that the information about the automation's functionality that different drivers require is dependent on their level of trust in the automation—the more trust the drivers have in the automated system, the less information the driver requires of the system. The driver's level of trust in the automation, however, is dependent on their use of the system, as over time drivers become more familiar with the automation, and then develop a higher level of trust in the automation. Regardless of how trust changes the amount of information drivers require of the automation, all drivers in the study requested information regarding the “degree of certainty that the automation is able to handle the current situation”. And therefore (though not entirely due to this study), there has been a push to investigate the use of displays that indicate system limits, and system certainty of handling different situations.

In order to combat some of the issues previously discussed with the TOR, some researchers have created uncertainty displays (Beller et al., 2013) and monitoring requests (Gold, Damböck, Bengler, et al., 2013) in an attempt to improve the driver’s situation awareness and knowledge of the automation’s fallibility. The displays that each group of researchers created were very similar to a TOR, however, a transition of control was not necessarily required. The uncertainty display used in the experiment performed by Beller et al. (2013) consisted of a cartoon face with a questioning look that appeared on the dashboard 3s prior to an ACC uncertainty situation (see Table 2), and informed the driver that the system was uncertain of its ability to handle the upcoming situation. The drivers were only using longitudinal automation, and only a fraction of the situations that the driver encountered were critical and required participant intervention. The results for the uncertainty display showed that when the display was present, participants’ minimum time to collision (TTC) increased by 1.1s on average, thus decreasing situation criticality. Additionally, the driver’s situation awareness, knowledge of the automation’s fallibility, trust, and system acceptance also increased. The monitoring request implemented by Gold, Damböck, Bengler, et al. (2013) consisted of an auditory-visual request that appeared 6s prior to a system uncertainty event (see Table 2). Drivers in this experiment were driving a highly automated vehicle that did not require the driver to monitor the road until a monitoring request appeared. Only a fraction of the events where the driver was presented with a monitoring request required participant intervention. As the experiment only compared the use of the monitoring request in highly automated driving to manual driving, it is not possible to determine the impact of the display on automated driving. However, participant’s subjective ratings of the monitoring request did show that it was useful and comfortable. While these are only two experiments on the use of uncertainty displays, they each appear to show a benefit to increasing automation transparency.

Research in the aviation industry has shown that there also is a benefit of providing operators with continuous feedback on automation performance, as operators develop a more appropriate level of trust in the automation than operators who do not have continuous feedback (McGuirl & Sarter, 2006). Therefore, another group of researchers have looked into providing drivers with displays that constantly provide drivers with information about the limits of the vehicle automation. Researchers have implemented these continuous feedback displays in different manners, and results indicate that they each aid drivers to have more effective transitions of control. Seppelt and Lee (2007) designed a dynamic display that continuously showed ACC limits to drivers (see Table 2 for more detail). While the display was complex, and thus difficult for drivers to easily comprehend, the visual representation of the ACC behavior nonetheless did promote appropriate reliance upon the ACC, and did support effective transitions of control, especially in traffic situations. When the display was present, participants braked faster and more consistently, which resulted in safe following distances and no collisions. These results show a benefit of continuous feedback.

Supplementing the research of Seppelt and Lee (2007), Helldin et al. (2013) designed an uncertainty display that continuously showed the level of the automation's reliability out of seven different levels, and the reliability correlated with the visibility (or lack thereof) outside of the car (see Table 2 for more detail about the design of the display). If the automation's reliability was above the threshold, then drivers knew they could still use the automation. Their results show that when it was necessary for drivers to takeover control, drivers with the uncertainty display took over control significantly faster than those without the display, and they trusted the automation less. While the reliability display in this experiment did appear to improve safety, drivers with the display also increased their secondary task performance, which indicated that they monitored the road less when the reliability display was present. This outcome appears to contradict the results of Beller et al. (2013), however, as participants in experiment performed by Beller et al. (2013) only used longitudinal automation, while participants in the experiment performed by Helldin et al. (2013) used both lateral and longitudinal automation, drivers may have reacted differently in each experiment due to the impact of level of automation on their monitoring. Additionally, participants in the experiment performed by Helldin et al. (2013) may have felt more comfortable partaking in the secondary task more often than the participants in the experiment performed by Beller et al. (2013), as they were provided with continuous information about the state of the automation, which, if regularly monitored, would provide the participants in the Helldin experiment with more advanced notice of system uncertainty than the 3s provided by the uncertainty display in Beller et al. (2013).

Stockert, Richardson, and Lienkamp (2015) also developed two displays that provided drivers with system confidence information (SCI) on the ACC's performance that showed to be effective (see Table 2 for more information). The most effective display that they developed included a SCI bar underneath the vehicle's speed information that showed the drivers three different levels of the automation's reliability. When the bar was green, the ACC was reliable, when the bar was yellow, it was less reliable, and when the bar was red, it was no longer reliable. This display proved to decrease the brake reaction time in the case of automation failure by an average of 4 seconds in relation to the baseline drive without the display. When the display was present, drivers decreased their interaction with the secondary task, which may result in an increase in situation awareness, and they also had an increase in ACC trust. It is interesting to note how the drivers decreased their interactions with the secondary task in this experiment, which is consistent with the results of Beller et al. (2013), but is contradictory to the results of Helldin et al.

(2013). This inconsistency can indicate that when designing reliability displays, the amount of information on the display that is provided may be of importance, as well as the level of vehicle automation.

One thing that was not addressed in these above studies on these informational displays is how they each impact the driver's monitoring ability. A recent study performed by Kraft, Naujoks, Wörle, and Neukum (2018) attempted to address this issue by evaluating a complex Head Up Display (HUD) with six individual indicators that informed drivers of whether the automation recognized all the relevant information it needed in order to function properly, such as the lead vehicle or the lane markings, against a simplified HUD display that only indicated the status of each of the vehicle's automated systems (see Table 2 for more details on the displays that were used). The researchers determined that the more complicated display did have a higher level of driver acceptance, however, drivers spent significantly more time monitoring the display than the road. The researchers therefore concluded that when designing displays, it is necessary to consider the amount of information that is being provided to the drivers.

While each of the display designs discussed above were implemented in very different manners, informing drivers about the status of the automation continually throughout a drive may be more effective than only warning drivers when the automation has reached its limit. Depending on the amount of information that drivers were provided, these displays were shown to help drivers improve the driver's reaction time to possible failure events. However, as each of the displays that have been researched thus far are very different, additional research is required to verify the impact of these displays on driver's monitoring strategy. Additionally, while these displays each appear to be beneficial, as of yet, there has not been a direct comparison between these displays and the TORs.

Table 2: Description of different reliability and informational displays that have appeared in research

Citation	Modality	Automation	Display Design
(Beller et al., 2013)	Visual	Longitudinal	Uncertainty display was in the form of a face expressing confusion. It appeared on the dashboard 3s prior the system uncertainty event, which was the lead vehicle appearing.
(Gold, Damböck, Bengler, et al., 2013)	Visual, Auditory	Lateral and Longitudinal. Driver is not required to monitor until request	Monitoring request (MR) occurred 6s prior to a system uncertainty event in the form of a symbol on the dashboard and an acoustic sound. The MR asked the driver to monitor the situation and takeover if the situation becomes critical.
(Seppelt & Lee, 2007)	Visual	Longitudinal	Graphical representation of the ACC limits were continuously displayed to the driver on an additional display mounted on the car's dashboard. The display was complex, and changed in shape and size depending on where the car was relative to

			the ACC's limits.
(Helldin et al., 2013)	Visual	Lateral and Longitudinal	Graphical representation of the automation's reliability was continuously displayed on the car's dashboard. The display consisted of 7 vertically stacked boxes that filled when the automation increased reliability, and emptied when the automation decreased in reliability (7 is high reliability, while 1 is no reliability). A red marker was placed next to level 2 to indicate the threshold of where the automation's performance could no longer be guaranteed.
(Stockert et al., 2015)	Visual	Longitudinal	System Confidence Information (SCI) was continuously displayed as a heads-up display. The top component of the display consisted of three components that informed the driver of: (1) whether the ACC is on or off, (2) the current vehicle speed, and (3) the speed limit. Underneath this information, two different SCI shapes were tested (a bar or a triangle). If the system was confident, the SCI shapes were green. At unclear situations, SCI drops from green, to yellow, and finally to red, which indicates a takeover situation.
(Kraft et al., 2018)	Visual	Lateral and Longitudinal	Two different human machine interfaces (HMIs) were tested (full and reduced), and each continuously displayed information to the driver from an additional monitor on top of the test vehicle's center console. Full HMI: presented driver with system status information, specifically (1) lead vehicle recognition, (2) ACC set headway distance, (3) lane marking recognition/ driver override of LK, (4) LK state (active, passive or standby due to lost lane markings), (5) ACC state (active, passive or standby), (6) ACC set speed. Reduced HMI: presented driver with basic system status information, specifically (1) LK status, (2) ACC status, (3) ACC set speed

2.3.4 Driver Experience and Training

For automated vehicles that are currently available on the market, drivers are not trained on how to use the vehicle's automation. In fact, in a publication from 2008, 70% of drivers have been found to not be aware of the manufacturer limits for these systems (Jenness et al., 2008). This number may be even higher given the proliferation of these systems in the past decade. This presents issues because the driver's reliance upon a vehicle's automation is significantly impacted by their preconceived notions of the automation's functions, as well as any information about the automation that drivers are provided prior to driving (Koustanaï, Cavallo, Delhomme, & Mas, 2012).

Given the influence of driver knowledge upon automation reliance, researchers have looked into the impact of training and familiarization upon driver's automation reliance. Payre et al. (2016) have shown that when drivers practice using the automation, the negative impact of over-trust on the driver's reaction time is mitigated. Additionally, training the drivers on how to use the automation, and how to recover control of the vehicle at failure events has been shown to improve the driver's reaction time and decrease the driver's number of interactions with the brake pedals, and increased driver trust in the system (Payre, Cestac, Dang, Vienne, & Delhomme, 2017). When drivers were familiarized with TORs, participants had significantly shorter takeover times, longer TTCs, and an increased trust in the automation (Hergeth, Lorenz, & Krems, 2017b). As training, familiarization, and practice with using vehicle automation have been shown to improve the driver's takeover quality, the author of this thesis decided that drivers in her experiment (see Chapter 3 for details on experiment design) receive a detailed explanation on how to use the automation prior to the experimental drives.

2.4 Research Gaps and Experimental Objectives

2.4.1 Objective 1—Failure Type Comparison

Given the literature review above, one pattern that has emerged is how drivers process anticipatory information about the automation's capabilities, i.e. how drivers process predictable failure events as compared to unpredictable failure events. While there has been some research where automation failures were clearly visually presented, such as a stranded vehicle in the ego lane (e.g. Gold, Körber, Hohenberger, Lechner, & Bengler, 2015), as of yet, there has not been significant research that has looked at the impact of these external indicators of a potential failure event on a driver's takeover quality. Thus far, most of the research has focused on the impact of different levels of traffic on a driver's takeover ability (Dogan et al., 2017; Gold et al., 2016; Jamson et al., 2013; Radlmayr et al., 2014), and has shown that while drivers may monitor the road longer in higher traffic situations, there still is a deterioration in the driver's takeover performance. Other research has looked at the impact of the type of automation failure—high road curvature, missing lane lines, or temporary lane lines—and has shown that the automation failure type does not impact the driver's takeover quality as the drivers did not understand why the TOR was issued (Naujoks et al., 2017). While this may have occurred because the TOR was issued at the location of the failure event, it may have also occurred because none of the drivers were briefed on the limits of the automation prior to the experiment. Previous research has shown that training and explaining the underlying logic of the automation improves the human-automation performance (Payre et al., 2017). Therefore, as stated earlier, for this research, it was decided that participants would be trained on the limitations of the automation prior to the experiment.

The work of Dogan et al. (2017) has shown that when drivers were briefed on the limits of the TJA, and they received anticipatory information that is salient, such as the speed of the vehicle increasing, drivers monitored the speed of the vehicle to prepare for an impending takeover event. However, as drivers had to look down towards the dashboard for the speed information, this additional monitoring did not impact the driver’s takeover quality. Nevertheless, this research shows that if drivers understand the limits of the automated vehicle system that they are using, and can see an impending automation limit, they may monitor the road more frequently, which may therefore improve their takeover quality.

Therefore, the first independent variable of interest in the simulator study that was conducted for this thesis is “failure type: predictable vs. unpredictable”. Participants were trained on the automation’s limits prior to the experiment, and they were taught to recognize the cues that would indicate different predictable failures. During the experiment, however, participants would only experience one of the predictable failures that they learned about. In order to provide participants with a distraction that is similar to ones drivers would partake in during real-world automated driving, participants could engage in a self-paced, visual-manual secondary task.

Given the literature review findings cited above, the following hypotheses were created:

H1: Participants will prepare and takeover sooner at predictable failure events than at unpredictable failure events, as they will be able to see the impending failure.

H2: Participants will exhibit a better takeover quality at predictable failure events than unpredictable failure events. This hypothesis is supported by the fact that when drivers are briefed about the limits of the automation prior to the drive, they are likely to monitor and look for that information (de Winter et al., 2014).

H3: Participants will decrease their rate of secondary task interactions when they approach predictable failure events. This hypothesis is supported by the results of Dogan et al. (2017) who found that their participants monitored the speed more as the vehicle’s speed was increasing towards the TJA’s limits, which would then translate into less usage of a visual-manual secondary task.

H4: Participants will have a higher acceptance and trust of the automated system during predictable failure events as drivers will better understand why the automation failed (Payre et al., 2017).

H5: Participants will have greater situation awareness at the predictable failure events. This hypothesis is supported by the work of Dogan et al., (2017) who show that drivers increased their monitoring of the speedometer as the vehicle’s speed was increasing towards the limit of the TJA. As a decrease in monitoring leads to a decrease in a driver’s situation awareness (Stanton & Young, 2005), the possible increase in monitoring should subsequently improve the participants’ situation awareness.

2.4.2 Objective 2—Display Comparison

Another research gap that emerges from the above literature review is in the development of methods to keep the driver in the loop and properly calibrate the driver's trust in the automation's capabilities in order to enhance situation awareness, driver understanding of automation, and consequently take over time and quality. So far, research has focused on TORs to get drivers back into the loop by requesting drivers to takeover control of the vehicle (Damböck et al., 2012; Gold, Damböck, Bengler, et al., 2013; J. Lee et al., 2006; Melcher et al., 2015; Naujoks et al., 2017), and on informational and reliability displays to keep the drivers in the loop by calibrating the driver's trust to the automation's capabilities (Beller et al., 2013; Gold, Damböck, Bengler, et al., 2013; Helldin et al., 2013; Kraft et al., 2018; Seppelt & Lee, 2007; Stockert et al., 2015).

Previous experimental work has also shown that drivers monitor in-vehicle anticipatory information (Dogan et al., 2017). However, the driver's increased monitoring did not impact their takeover quality as they were required to look down towards the dashboard for this information. Therefore, for the experiment of this thesis, all visual displays were presented as a heads-up display (HUD), and therefore were on the windshield.

As of the time when this thesis was written, there have not been any comparisons between TORs and informational/ reliability displays. Therefore, one of the goals of this research was to develop a reliability display that would be present throughout the entire drive, and would present the capabilities of the automation to the driver, in order to analyze how such a display would compare to TOR. Thus, the second independent variable for the simulator study reported in this thesis was "display type: TOR vs. reliability". Given the literature review findings cited above, the following hypotheses were created:

H6: Participants will takeover sooner when the reliability display is present than when the TOR display is present. This is expected because when drivers see the level of the automation's reliability decreasing, they will increase their monitoring frequency, and possibly look towards the road to see why the automation's reliability is decreasing. By increasing the monitoring frequency, the driver's takeover time should decrease (Merat et al., 2012).

H7: Participants will exhibit a better takeover quality with the reliability display, as they will have a more properly calibrated trust to the environment, and therefore monitor the environment more regularly. This is hypothesized because the results of previous research has shown that the extent to which driver's trust the automation impacts their monitoring, and thus their takeover quality (Beggiato et al., 2015; Hergeth et al., 2016; Körber et al., 2017).

H8: Participants will have a higher level of system acceptance with the reliability display than with the TOR. This is expected as previous research has shown that displays with more information and system limits showed a higher acceptance among (Kraft et al., 2018). Other research has shown that while TORs were beneficial to a good takeover, participants would have preferred additional information about the limits (Naujoks et al., 2017).

Chapter 3

3 Methods

A driving simulator study was conducted to address the two objectives introduced in the section above. Participants completed four experimental drives which involved following a lead vehicle and performing a self-paced visual manual secondary task (section 3.8).

Participants had no prior knowledge or experience with the ACC or LK systems. In order to guarantee that all participants had the same knowledge of automated driving prior to the experimental drives, each participant received the same comprehensive training session. During the training, participants learned how to use automation, which in this experiment consisted of the ACC and the LK systems (section 3.6). Participants were also briefed on the limits of both the ACC and LK systems to give them the knowledge to recognize predictable failure events (section 3.9). Subsequently, participants were tested on their knowledge of the system limits to verify their understanding. Prior to the first experimental drive, all participants performed a training drive where they experienced an unpredictable failure and a predictable failure (section 3.9, step 5).

In order to assess the impact of failure type on a driver's takeover quality, each of the participants drove two scenarios without a display present—one where the participant experienced predictable failures (section 3.5.1), and another where the participant experienced unpredictable failures (section 3.5.2). For the other two experimental drives that participants performed, half of the participants performed the aforementioned predictable and unpredictable scenarios with a TOR present (section 3.4.1), and the other half performed them with a reliability display present (section 3.4.2). Before each block of drives with a display present, participants were introduced to the display that they would be using.

3.1 Participants

36 participants (19 males, 17 females) participated in this experiment. Participants were recruited through online job postings, email listservs and poster advertisements (see Appendix A). Participants were between the ages of 25 and 30 ($\bar{x}$=27.5, SD=1.54), had a valid full Canadian driver's license or equivalent for at least 2 years, drove at least several times a month, and had normal or corrected-to-normal vision. Participants were selected based on their responses to a screening questionnaire (see Appendix B). The intent of the screening questionnaire was to 1) avoid recruiting participants who were prone to simulator sickness, and 2) only recruit individuals who had no previous experience driving with Adaptive Cruise Control (ACC) or with Lane Keeping (LK). As ACC and LK systems are relatively new and not standardized among different vehicles, and as the majority of the population does not have experience

with these technologies, the author decided that the simplest way to guarantee a similar knowledge background among participants was to only recruit drivers with no prior vehicle automation experience. Participants were compensated at a rate of $14/hour plus an $8 bonus. Participants were told that the bonus was based on secondary task engagement and driving performance, however each participant received the full bonus.

3.2 Apparatus

A NADS quarter-cab MiniSim^{TM} Driving Simulator was used for the study (Figure 2). This fixed-base simulator has three 42” widescreen displays, creating a 130° horizontal and 24° vertical field of view at a 48” viewing distance. The simulated driving experiment was developed using the MiniSim Software Suite. The road network was created using a roadmap provided by MiniSim, and the driving scenarios were created using the Interactive Scenario Authoring Tool. The simulator collects driving measures at 60 Hz.

While a driving simulator may not provide results that are as realistic as using an automated vehicle for experimentation, the use of a driving simulator for this study is comparable to previous research in this domain, as the majority of the research has been performed using driving simulators.

The self-paced visual-manual secondary task (described in section 3.8) was displayed on a Microsoft Surface Pro 2 positioned to the right of the dashboard where it would not be visually obstructed by the steering wheel. A head-mounted Dikablis Glasses 3 eye tracker was used to collect gaze data (Figure 2), and electrodes were used to assess a driver’s heart rate via electrocardiogram (ECG).

Figure 2: Simulator set up with Surface Pro 2 (1) for the secondary task, and a Dikablis eyetracker (2)

3.3 Experiment design

The experiment used a 2x2x2 mixed design with display type (TOR or reliability display) as a between subject variable, and display presence (yes or no) and failure type (predictable or unpredictable) as within-subject variables. Given that display type was a between-subjects variable, participants experienced either of the displays but not both.

Each participant completed four experimental drives. These drives were blocked into two groups; in one block of drives, there was no display present, in the other block, a display was present. In the block where a display was present, it was either the TOR or the reliability display depending on the display type condition assigned to each participant. The order of these blocks was counterbalanced across participants. Within each block of drives (2 drives per block), participants completed one drive where they experienced predictable failure events, and another where they experienced unpredictable failure events. The order of the drives was also counterbalanced across participants for failure type. The counterbalanced design therefore consisted of 16 different orders for the experimental drives that each participant could experience. Participants were randomly assigned to an order of experimental drives using a random number generator (Appendix C).

3.4 Displays

There were two different displays that were tested in this experiment—the Take-Over Request (TOR) and the reliability display. These two different displays defined the two experimental groups into which participants were divided, making the display type the between-subject variable. 19 participants experienced the TOR display, while 17 participants experienced the reliability display.

3.4.1 Take-Over Request (TOR) Display

Similar to a warning signal, a TOR is a tool that is used to warn drivers of an impending issue with the automation by informing drivers that they need to resume control of the vehicle. In the literature, TORs often appear 3 to 8 seconds prior to an automation failure event, with a mean TOR lead time of 6 seconds (Eriksson & Stanton, 2017b). In this experiment, the TOR appeared 6 seconds prior to an automation failure event. This number was chosen as it is a conservative estimate for automated vehicle sensor limits (the manual for the Tesla Model S Forward Collision Warning System specified that the system could monitor up to 160 m in the driving path, and therefore if the vehicle is driving at 50 mph, a sensor would be able to alert the driver 7 seconds in advance).

The TOR that was used in this experiment consisted of both visual and auditory stimuli as drivers have a faster reaction time when a warning consists of both an auditory and visual warning rather than just a visual warning (Naujoks et al., 2014). The auditory component of the TOR consisted of a loud beep that lasted for 2 seconds and had a rate of 3 Hz. The visual component of the TOR is shown in Figure 3, and the view of the TOR in the simulator from the driver's perspective is shown in Figure 4. The design of this display was inspired by previous works, which included a steering wheel grasped by hands (Eriksson & Stanton, 2017b; Melcher et al., 2015; Naujoks et al., 2014; Zeeb et al., 2016). As the TORs in some of the previous work were red, the hands on the original TOR for this experiment were red. However, after pilot testing the original designs in the driving simulator with human factors experts, it was determined that the hands should be orange, because the color red could be interpreted as automation failure in progress/take immediate action. The color orange, however, would convey caution, and inform participants that they should prepare for an impending failure by taking over control.

In order to keep TOR in the participant's main field of view and in close visual proximity to the secondary task, the TOR display appeared in the lower right hand corner of the center monitor, and had a visual angle of ~2.08° at a distance of 55". Once the display appeared, it remained on screen for a total of 26 seconds (6 seconds prior to the failure event and 20 seconds after the failure event). The TOR remained present for an additional 20 seconds to make sure that participants would not turn the automation back on immediately after a failure event, and allow for the measurement of take-over quality, such as the standard deviation of steering[3].

For the participants who were assigned to experience the TOR display condition, prior to commencing the block of two drives where the TOR display would be present , participants were taught how to use and interpret the TOR display. Participants were told "*In the next two drives, you will be using this display called the Take-Over Request, also known as the TOR. As you already know, the automation is not perfect, and it has limitations. This display, along with a loud beeping sound, will appear here 6s prior to an instance where the automation will have difficulties* <point to where on the screen the TOR will appear>. *Essentially, it is telling you that there will be an issue with the automation, and you should take-over control of the vehicle. The display will remain present until it is safe to turn the automation back on.*"

Figure 3: Take-Over Request (TOR) display

[3] 20 seconds was chosen in order to make the measurement of the standard deviation of steering consistent with previous work, such as the work of Eriksson & Stanton (2017a), and with the definition of this metric (as defined in section 4.1).

Figure 4: View of TOR display on the center monitor from the perspective of the driver. The TOR is at the bottom right of the screen.

3.4.2 Reliability Display

The reliability display was developed to provide drivers with continuous feedback about the state of the automation, specifically how reliable the vehicle's automation was at a given point in time. The reliability display designed for this experiment (Figure 5) was taken from the work of Helldin et al. (2013), with the only difference between the displays being the vehicle graphic that was used, and the location of the display Helldin et al. (2013) put their display on the dashboard, while the display in this experiment is on the monitor as a heads-up display). The display has seven levels of reliability. While Figure 5 depicts each of the levels with a black outline, the levels each had a white outline in the simulator, and that improved the contrast between the display and the background. When each of the levels are blue (Figure 5, left side, and Figure 6), the automation is fully reliable. As the bars in the reliability display decrease, the automation becomes less reliable; however, it is still safe for a participant to use the automation up until the threshold, which is denoted by the red line and triangle in the display. Once the automation's reliability is below the threshold, the entire display turns orange (Figure 5, right side, and Figure 7). This means that an issue with the automation will occur.

In order for the reliability display to be directly comparable to the TOR, the reliability of the automation went below the threshold 6 seconds prior to an automation failure event, accompanied by a loud beep that lasted for 2 seconds and had a frequency of 3 Hz.

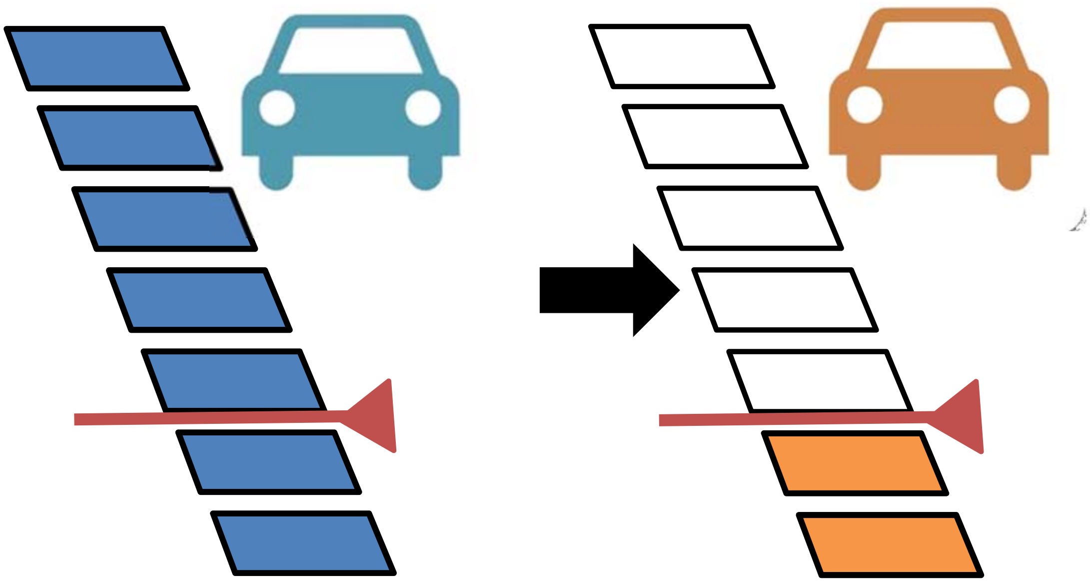

Figure 5: Reliability Display. The left image shows the reliability display at Level 7. The right image shows the reliability display at Level 2, which is below the threshold.

Figure 6: View of the reliability display at Level 7 on the center monitor from the perspective of the driver. The reliability display is at the bottom right of the screen.

Figure 7: View of the reliability display at Level 2 on the center monitor from the perspective of the driver. The vehicle is at an intersection here. The reliability display is at the bottom right of the screen.

While the TOR only appeared 6 seconds prior to a failure event, the reliability display was present for the duration of the experimental drive. At the beginning of each drive, the reliability display was at Level 7. After nearly a minute of driving, the reliability display decreased to Level 6. As the vehicle approached a failure event, the reliability display continually decreased in reliability until the vehicle was 6 seconds away from the failure event, which was when the reliability was at Level 2 (below the threshold). The timing for the decrease in the levels of reliability prior to a failure is documented in Table 3. The timings were determined based on pilot studies in the driving simulator with graduate students studying human factors. The goal of these timings was to produce a gradual decrease in the reliability rather than a rapid decrease, to enable participants to see the vehicle's reliability change. As one of the purposes of this experiment was to evaluate the difference between the TOR and the reliability display, it was determined not necessary to have a direct reason external to the vehicle for when the automation's reliability begins to decrease. However, at predictable failures, a plausible reason for the decrease in the automation's reliability could be the fact that often times road are mapped, and therefore, if the automation knows of an upcoming intersection, it would be able to warn the driver well in advance. As unpredictable failures are simply failures that are unpredictable from the perspective of the driver, there still could be an external reason as to why the automation's reliability is decreasing. The timing of when Level 6 occurred prior to a failure event is not included in Table 3 because it was triggered to appear in a different manner than the other reliability levels, specifically, its appearance was based on the ego-vehicle reaching a certain point on the road rather than reaching a certain time from the failure.

After the failure, the reliability display remained at Level 2 for an additional 20 seconds to dissuade participants from turning the automation back on immediately subsequent to the failure event, and allow for the measurement of take-over quality. After these 20 seconds, the reliability display gradually climbed again. The timing for the increasing the levels of the reliability display after a failure event is recorded in Table 4. The timing for when Level 7 reappeared after a failure event is not included in Table 4 as it was triggered to appear in a different manner than the other reliability levels, specifically, its appearance was based on the ego-vehicle reaching a certain point on the road rather than reaching a certain time after the failure event.

In order to keep the reliability display in the participant's main field of view and in close visual proximity to the secondary task, throughout the drive the reliability display was located on the bottom right hand corner of the center monitor, and it had a visual angle of 3.64^{o} at a distance of 55".

Table 3: Reliability Level prior to a failure event

Reliability Level	Seconds Prior to Failure
Level 5	26 seconds
Level 4	20 seconds
Level 3	14 seconds
Level 2	6 seconds

Table 4: Reliability Level after failure event

Reliability Level	Seconds After Failure
Level 3	20 seconds
Level 4	23 seconds
Level 5	26 seconds
Level 6	31 seconds

For the participants who were assigned to experience the reliability display condition, prior to starting the block of two drives where the reliability display would be present, participants were taught how to use and interpret the reliability display . Participants were told, *"In the next two drives, you will be driving with a reliability display. This is the display. It will be present the entire drive, right over here* <point to

where on the monitor it will be>. *It tells you how reliable the automation is at any given point in time during the drive, and will warn you in advance if it senses a future issue with the automation. As you see in this image, there are seven levels for the reliability, and as the levels decrease, the reliability of the automation decreases. However, even though the reliability of the automation is decreasing, you can safely use the automation up until this red line. This line indicates the threshold where the automation will soon no longer be reliable. When the reliability is below this threshold, there will be a loud beep, and the display will turn orange. This means that in 6 seconds from now, there will be an issue with the automation, and you should take-over control of the automation. However, you don't have to wait until the reliability is below the threshold to take-over control—you can do it whenever you think it is necessary to drive safely."*

It is necessary to note, however, that while the intent of Objective 2 is to compare these displays, the reliability display as it is designed does not provide a fair comparison to the TOR. This is because every decrease in the reliability display led to a failure event, simply increasing the length of time that participants could prepare for a failure event relative to the TOR. This was an experimental design choice. Future experimentation should use reliability displays that increase and decrease throughout the drive, not just decrease prior to failure events.

3.4.3 No Display Present

As mentioned earlier, each participant also drove a block of two drives without a display present. This was the baseline condition. At the beginning of this block of drives, if it was subsequent to a block with the display present, participants were told, *"In the next two drives, you will be driving without out any additional displays, just like in the first drive that you performed."*

3.5 Failure Type

There were two different failure types that were examined in this experiment—predictable and unpredictable failures (explained below). This was a within-subject variable, with one predictable failure drive and one unpredictable failure drive per block. Thus, each participant experienced two drives with predictable failures and two drives with unpredictable failures. Each drive had two failures, both of the same type.

At the time of the development of the experiment, it was not possible to create longitudinal failures with the MiniSim driving simulator, such as the ACC not recognizing static objects in the ego-lane, or lead vehicle cut-in events. This was because the MiniSim driving simulator did not have the capability of controlling the ACC's behavior at the time of the development of this experiment. Given this limitation in the driving simulator, each of the failures that are described below are in the lateral direction, as the behavior of the lane keeping system controlled in the simulator. The use of automation failures in the lateral direction has been previously verified in the work of Shen and Neyens (2014, 2017).

3.5.1 Predictable failures

Predictable failures are the failures where a driver, based on their knowledge of the automation, is able to look at the road and understand why the automation is not performing well. This means that there are external indicators for the automation's poor performance that a driver can perceive in advance of a potential issue. An example of a predictable failure could be bad weather, or a stationary car in the ego lane. In this experiment, as it was only possible to create lateral failures, and as the experimenter wanted to take advantage of inherent flaws in the function of the simulator to make the failures that occur appear as they would in a normal driving environment (i.e. make them as simple as possible, without adding people or trucks to the scenario, which can appear out of place), the predictable failures occurred at intersections with right turn lanes. The inherent flaw with the simulator was that at these intersections, when the lane keeping was engaged, rather than continuing straight to follow the lead vehicle, the ego-vehicle would go into the turn lane. As participants were taught about each of the limits of the automation prior to the experiment (see section 3.9), participants knew that when the lateral automation was engaged the ego-vehicle may not continue straight through the intersection, and would rather follow the road edge line.

The occurrence of the predictable failure at an intersection has ecological validity with actual automation issues that have occurred. Specifically, it shares similarities with the cause of the Tesla crash in 2018, where the vehicle's lane keeping system followed the more visible lane keeping line, rather than following the vehicle in front of it. Additionally, the Tesla Model S Owner's Manual lists lanes changing quickly, such as lanes branching off, crossing over or merging as a limitation for Tesla's lane keeping system. While intersections are not specifically indicated as a failure event, the manner in which the intersection failure event progresses (described below) would fall under the limitation category of lanes changing quickly.

The first predictable failure event occurred at an intersection that was nearly 2230 m from the start of the drive. When the car approached the intersection, a right turn lane appeared, and rather than continuing straight through the intersection, the car followed the solid white line marking the edge of the pavement, and went into the turning lane (Figure 8). There was a road sign indicating the upcoming intersection 184m prior to the intersection. Additionally, as the participant approached the intersection, they could see a street light, as well as several buildings surrounding the intersection. As the rest of the drive was a rural landscape, if a participant was paying attention, they could notice the indicators of an upcoming intersection.

The intersection failure described above was created by not defining the path for the ego-vehicle. Without this path, the pre-programmed automation made the vehicle follow the road's edge line.

If a participant took over control of the automation prior to reaching the beginning of the right hand turn, the participant would simply drive the vehicle through the intersection. If the participant took over control of the automation after the start of the failure event, then the participant would steer the vehicle back into the center lane to follow the lead vehicle.

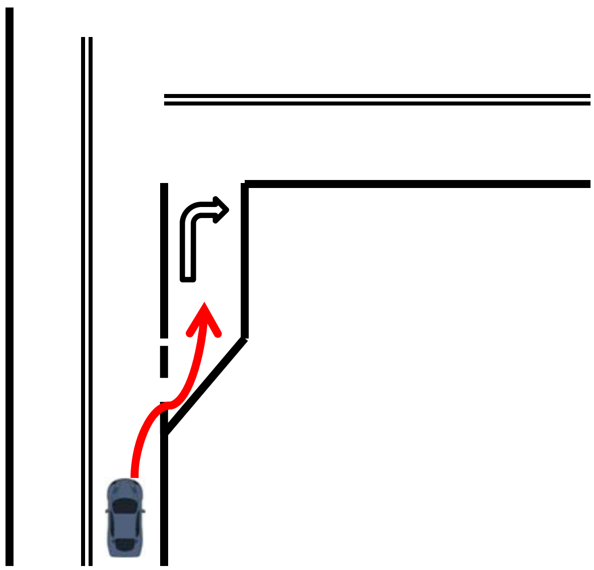

Figure 8: Path of the vehicle at the first intersection

A second predictable failure was also designed for this experiment. It occurred at a left-turn intersection. Given the limitations in designing a new road path with multiple intersections in MiniSim, the failure was 4734 m away from the first predictable failure. Unfortunately, the second predictable failure did not materialize as intended; it became clear during data collection that participants were not able to predict the second failure, and the manner in which the failure progressed was different from the other failures participants experienced during the experiment. Therefore, the second predictable failure was not included in the data analysis. For more information regarding the second predictable failure and why the second failures were not included in most of the data analysis, please see Appendix D.

3.5.2 Unpredictable failures

Unpredictable failures are the failures where a driver looks out on the road and does not understand why the automation is not performing well. Therefore, based on the driver's prior knowledge of the system, the driver does not expect the system to act incorrectly, and the failure was unpredictable to the driver. An unpredictable failure can occur for a variety of reasons, one of them being algorithm or sensor issues. An example of an unpredictable failure could be when the automation unexpectedly accelerates, or fails to brake.

In this experiment, in order to be comparable to the first predictable failure, the unpredictable failures also occurred with the lane keeping system. Additionally, the manner in which the vehicle failed was iterated upon until it was visually determined by the experimenter to have the same level of rapidness, and require a similar level of steering as the predictable failures. Both failures were therefore of a similar level of severity where participants would always react because the car would suddenly perform in an unexpected manner. For the final design of both unpredictable failures, the car veered to the right at an angle of 80°. Each unpredictable failure happened when the road was straight. The first unpredictable failure occurred at nearly 2168 m from the start of the drive. The two unpredictable failures were 3632 m apart from each other.

If a participant took over control of the vehicle prior to the failure event, the failure would not be triggered, and the participant would continue to drive. If the participant took over control of the vehicle after the start of the failure event, the participant would steer the vehicle back into the lane and continue driving. If a participant did not notice the failure and take-over immediately, the car would continue to go off road, and eventually hit the rumble strip, thus giving the participant an auditory cue that they went off road.

3.6 Automated Driving

In this experiment, participants used both the ACC and LK systems for a SAE Level 2 automated driving experience. Prior to driving with each of these systems, participants were trained to use them (see section 3.9 to understand how participants were trained). The MiniSim driving simulator had dashboard indicators the participants used to determine whether the ACC or the LK was engaged (Figure 9) or not engaged (Figure 10). Participants could turn on and set the ACC by pressing the buttons on the steering wheel, and could turn off the ACC by pressing the ACC cancel button on the steering wheel or by pressing on the brake. Participants could turn the LK on by pressing the LK On/Off button on the steering wheel, and participants could turn the LK off by pressing the LK On/Off button once again, or by turning the steering wheel 5° in either direction. Additionally, it is important to note that the steering wheel was unyoked, meaning that the steering wheel was not mapped to the movement of the wheels, when the LK was on due to the capabilities of the simulator. This was determined to be acceptable based on the work of

Kerschbaum, Lorenz, and Bengler (2014), as they showed the static steering wheel was not noticed by a majority of their participants, and that it had no effect on the driver's takeover time.

The capability for a participant to turn the LK off via turning the steering wheel was added after pilot testing showed that participants did not remember to turn the LK off using the LK On/Off button during unexpected failure events. The 5° threshold for turning the LK off via steering was also determined through pilot testing. When the threshold to turn the steering off was lower, participants regularly turned the LK off unintentionally when they put their hands on the wheel in the middle of a drive. When the threshold was 6°, or slightly larger, participants had more difficulty turning the LK off, and often went into the opposing traffic because they oversteered to correct for the failure event. In order to mitigate the aforementioned issues, 5° was determined to be the threshold for turning the LK off by steering.

Through pilot testing, it was also determined that a participant could only turn the LK on when they drove on straight roads. When the LK was set on a curve, the static steering wheel would remain in the last position that the driver set it to prior to turning the LK on. As this angle was regularly greater than the threshold, the algorithm that enabled the LK to turn off via steering would no longer work when participants attempted to steer to turn the LK off at the failure events.

Figure 9: Dashboard display showing the ACC and LK ON. (1) LK is on. (2) The ACC is on, and the set speed is 50 mph. The car indicates that the sensors sense the lead vehicle, and the line and the dot indicate the 3s headway gap that was told to the participants.

Figure 10: Dashboard display when both the ACC and LK are off. (1) The LK is off, as indicated by the lack of display. (2) the ACC is off, as indicated by no set speed. It also says "cruise ready", which means that participants can engage the ACC at any point in time.

3.7 Driving Scenario

Each of the drives where participants experienced predictable failures used the same road network; the only difference between the two drives with predictable failure events that a participant performed was whether a display was present. As the scenarios where drivers experienced unpredictable failure events could not have intersections in them, the drives where participants experienced unpredictable failure events used a different road network than the predictable failure drives. However, each of the drives where participants experienced unpredictable failures also used the same road network, with the only difference between the two drives being whether the display was present. While not ideal, as participants can recognize patterns and possibly identify the locations of the failure events, in order to be able to test each of the variables in the experiment, it was necessary for participants to complete the same road path for each drive with predictable failures and each drive with unpredictable failures. This was because, at the time that this experiment was designed, it was not possible to create comparable road paths, and maintain good lane keeping functionality[4]. Each drive took roughly six minutes to complete.

Each of the drives occurred on a rural two-lane highway, where the road was 12 feet across (3.66 m), and had double yellow lines separating the opposing lanes of traffic. The posted speed limit was 50 mph. The participant was instructed to follow a lead vehicle throughout the drive. The lead vehicle maintained a gap of 3 seconds to the ego-vehicle. This time gap was determined through pilot testing as there were participants who didn't feel comfortable accelerating to 50 mph when the gap was 2 seconds. This pilot

[4] With other road paths that were designed using the Tile Mosaic Tool (TMT), the lane keeping did not drive around curves in a fluid, continuous manner. Rather, the lane keeping went around curves in a very choppy way. During pilot testing, participants often took over when they experienced this choppiness as they felt that it was indicative of a potential failure in the lane keeping system.

test consisted of 13 people, most of whom were University of Toronto students unaffiliated with human factors research. There was regular traffic in the opposing lane, at a rate of roughly 9 to 11 cars per minute.

25 seconds after a participant started driving, an audio file played and told the participant "Please engage the automation." When a participant heard this, they would engage the ACC and the LK. If the participant was on a curve when the audio file played, the participant would wait to turn on the LK until they were at a straight road. This audio file also played 20 seconds after each failure event to inform the participants of when they could turn the automation back on.

3.8 Secondary task

Participants had the opportunity to engage in a secondary task for each drive that they performed. This was in order to provide drivers with the option of performing a non-driving task, similar to what they would have the option of doing were they in an automated vehicle. The secondary task that participants engaged in while driving in the simulator was a self-paced visual-manual task that was adapted from the work of Donmez, Boyle, and Lee (2007). This task's purpose was to mimic a how a person would interact with a vehicle's infotainment system. An example of a real interaction would be searching for a song to play. Donmez et al. (2007) showed that this secondary task significantly affected a driver's performance—drivers experienced longer accelerator release times when the secondary task was available as compared to the condition where there was no secondary task.

The task was a word matching task presented on the Surface Pro 2 (Figure 11). Out of a list of 10 closely related phrases, participants needed to select one correct phrase that matched the target phrase "Discover Project Missions". A phrase qualified as a match if any of these three conditions were met: "Discover" was in the first position, "Project" was in the second position, or "Missions" was in the third position. Thus "Discover Missions Project" is a match because it has "Discover" first, whereas "Project Discover Misguide" is not a match because none of the target words are in the correct place. Only two options were displayed on the screen at a time, and to scroll through the options, participants could tap the up and down arrows with their fingers. Participants entered their choice by pressing the submit button and received feedback on whether their choice was correct or incorrect. The task was available throughout the drive and participants could choose when to start a new task, and when to finish their current task.

Participants were told that their $8 bonus applied to their secondary task performance. Participants would receive $0.20 for each correct answer, and they would lose $0.40 for each incorrect answer. However, participants were also informed that their driving performance would be rated, and if their performance was poor, there would be deductions from their bonus. With this in mind, participants were told that they should driving safely, but that they also have an incentive to perform the secondary task. However, regardless of the driver's performance, at the end of the experiment, all participants received the full $8 bonus.

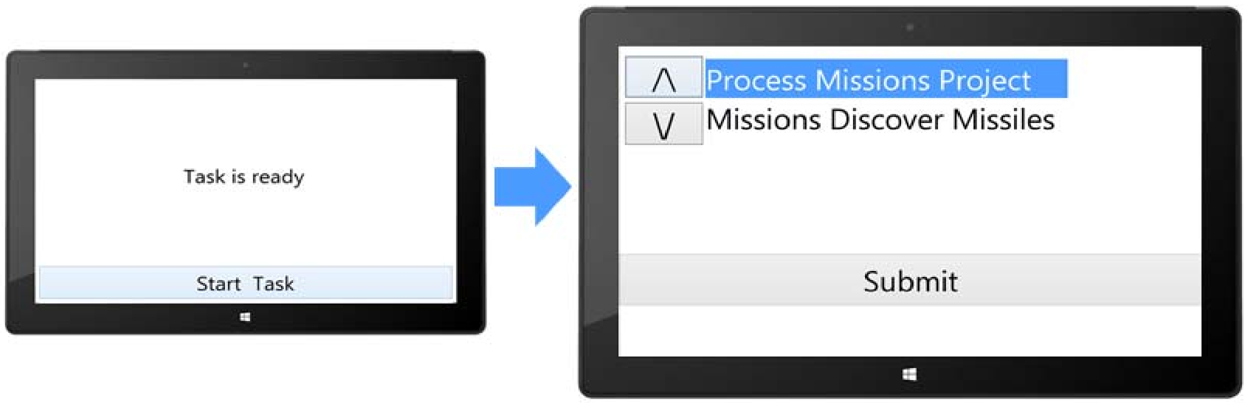

Figure 11: The secondary task as it appears on the 208 dpi Surface Pro 2

3.9 Training

Training the participants on how to drive with the automation was a multi-step process, and it utilized the PowerPoint slides shown in Appendix E. The steps are documented below:

Step 1):

Once the participant adjusted the seat and the steering wheel, they were told, "*As you know, you are participating in an automated driving study. However, as automation isn't perfect yet, the first thing I want you to practice doing is to drive the vehicle manually.* <point out the brake, accelerator, and the mirrors, etc.> *The car that you are driving will drive a bit more like a truck drives, which means that it is slow to accelerate and slow to decelerate, and the steering wheel will feel a bit more sensitive than most cars you may drive. Now I want you to drive the car."* <The participant will drive the training scenario for about 2 minutes.>

The road that was used for the training drives was a rural road with curves that was similar to the one used in the experimental drives.

Step 2):

Now the participant needs to learn about automated driving. *"So what do you already know about automated driving?* <listen to the participant's response> *Those are all parts of automated driving, but now I will teach you how to use the automation in this system. There are two systems* *that you will use in this experiment—the Adaptive Cruise Control, otherwise known as ACC, and the Lane Keeping system. First, I am going to teach you how to use the ACC. Have you ever used cruise control before? Well, ACC is very similar to cruise control, however, it has the added benefit of being able to maintain a set distance between your car and the car in front of you. In the case of this experiment, the distance is set to 3 seconds. If the car in front of you slows down, your car will also slow down to maintain that distance.* <Explain the ACC display, and how to set and cancel the ACC.>

While this system works well, given the manner in which the sensors work, there are some limitations: 1) The ACC only has 30% braking power, which means that if the car in front of you comes to an abrupt stop, your car will not be able to abruptly stop as well, 2) The ACC does not work well in poor weather, 3) The ACC does not detect pedestrians, motorcycles or other small objects on the road, and 4) Seemingly random failures may occur due to sensor or algorithmic failures. <Turn the PowerPoint away, and ask the participant to repeat the four limitations.>

Great, now here is a quick quiz. Will the ACC work in the scenario pictured here? <Go through the "Quick Quiz" for the ACC, and ask the participant whether the ACC will work in the shown situation, and have them explain their answer. If the answer is wrong, correct them.> *Great, now I want you to practice turning the ACC on and off in this training drive. First, get up to 50mph, and then I want you to turn the ACC on.* <Wait a few moments> *Now I want you to turn the ACC off using the cancel button.* <Wait a few moments> *Now I want you to turn the ACC back on.* <wait a few moments> *Now I want you to turn the ACC off using the brake pedal."* <Ask the participant to turn the ACC on and off two more times, or until the participant feels comfortable using the ACC.>

Step 3)

After learning about how to use the ACC, the participant needs to learn how to use the LK system. *"So you just learned how to use the ACC. Now I am going to teach you about how to use the Lane Keeping system. When the Lane Keeping is on, the car essentially is able to steer itself, and navigate both the straight roads, and the curved roads. The way the Lane Keeping system works is that it uses computer vision technology. There is a camera installed right behind the rear-view mirror, and it looks at the entire road—the white lines on both edges of the road, as well as the yellow line in the middle—and based on the road structure it sees, it is able to determine where the car should be on the road and steer the car.*

You can turn the Lane Keeping on and off using this button over here. Now if you look at the dashboard, you can see this indicator for the Lane Keeping. <Turn the LK on and off for the participant so they can see it turn on and off on the dashboard.> *In addition to turning the Lane Keeping off using the button, you can also turn the Lane Keeping of by turning the steering wheel* 5^o *in either direction, like this.* <Turn the LK on, and move the steering wheel in both direction to turn the LK off.> *As the steering wheel will remain stationary once you turn the Lane Keeping on, it is important to only turn the Lane Keeping on when you are on a straight-away, i.e. a straight portion of the road. When you turn the Lane Keeping on, you may have your hands near the wheel or completely off the wheel, but you may not have them on the wheel, because that means that you are about to disengage the automation.*

As the system must be able to "see" the road in order to function properly, the system has several limitations: 1) The Lane Keeping system does not function as well in poor weather, 2) The Lane Keeping system will not function as well if the lanes are not clearly marked, i.e. they are excessively worn, or adjusted due to construction, 3) the Lane Keeping system does not function as well if the lane markings change quickly, either due to construction or at intersections, and 4) Seemingly random issues may occur either due to sensor errors or algorithmic failures. <Turn the PowerPoint around and ask the participant to repeat the systems limitations.>

Great, now here is a quick quiz. Will the Lane Keeping system work well in this scenario? <Go through the "Quick Quiz" for the LK, and ask the participant if they think the LK will work in the displayed situations, and have them explain their answer. If the answer is wrong, correct them.> *Great! Now I want you to practice turning the Lane Keeping on and off in this training drive. First, get up to 50mph and turn the ACC on. And then, when you are at a straight road, I want you to turn the Lane Keeping on.* <Wait a few moments.> *Now I want you to turn the Lane Keeping off using the button.* <Wait a few moments.> *Now I want you to turn the Lane Keeping back on.* <wait a few moments> *Now I want you to turn the Lane Keeping off by steering to the right."* <Ask the participant to turn the Lane Keeping on and off 3-6 more times, each time changing the manner in which the participant turns off the LK (button, steer to the left, or steer to the right). Do this until the participant feels a bit more comfortable using the system.>

Step 4)

Now that the participant knows how to use both the ACC and the LK, it is necessary to train them on how to perform the secondary task. The information for training a participant on how to use the secondary task is located above in section 3.8. At the end of the training, the participant was told, *"Now that you know how to do the secondary task, I want you to practice doing the secondary task with the automation on. In this drive, I only want you to turn on the automation when I say 'Please engage the automation'. Also, please remember to only turn the Lane Keeping on when you are driving on a straight-away. And don't forget to do the secondary task when you feel safe to do it."* Have the participant do a final training drive from their point of view with the ACC and the LK engaged, while also performing the secondary task. Make the participant turn off all of the automation twice during the drive.

Step 5)

Verify that the participant does not feel nauseous after all this training. Set the participant up for what they think is the first experimental drive, but is really another training drive. This training drive lasts for nearly 6 minutes, and has the same structure as the experimental drives that were described above. There is no display present in this training drive, and the participant is introduced to unpredictable and predictable failures. This training drive was performed so that the first failures that participants encounter in the experimental drives would not be influenced by the confusion or shock a participant may feel during their first encounter with each failure.

In order to decrease the likelihood of participants recognizing external cues for the predictable and unpredictable failures they would experience during the experiment, this training drive occurred on a different roadway. Given the design of this roadway (specifically, its length, and location of its intersection), it was necessary to make the first failure that participants encountered in the drive the unpredictable failure, and the second failure the predictable failure.

3.10 Procedure

Prior to starting the experiment, the experimenter guided the participant through informed consent (Appendix F). The experimenter then explained that the participant would be driving five experimental drives, and then subsequently went through steps 1 through 3 of the training in section 3.9. After those steps were completed, the participant completed a Pre-Experiment Questionnaire (Appendix G). This questionnaire included a questionnaire that assessed a participant's potential to be complacent towards the use of automated technology (Singh, Molloy, & Parasuraman, 1993), and another questionnaire that assessed the extent of a participant's trust of the automated driving system they just learned about (Jian, Bisantz, & Drury, 2000b). The full training took between 30 to 40 minutes. Subsequently, step 4 of the training in section 3.9 was completed, and participants were then guided through the use and calibration of the eye tracker, and the ECG sensors. Next, step 5 (which includes the six minute training drive) of section 3.9 was completed. After the training drive, participants were asked to complete a Within-Experiment Questionnaire (Appendix H). This questionnaire was made up of the following five questionnaires: 1) NASA-TLX to assess perceived workload (Hart & Staveland, 1988), 2) Perceived Risk to assess how risky the participant perceived the driving scenario to be (Tsimhoni, Smith, & Green, 2003), 3) Situation Awareness Rating Technique (SART) to assess a participant's situation awareness during the scenario (Taylor, 1990), 4) Trust to assess the extent to which a participant trusted the automated system that they used (Jian et al., 2000b), and 5) Acceptance to assess two components of acceptance—usefulness and satisfaction (Van Der Laan, Heino, & De Waard, 1997).

After the Within-Experiment Questionnaire for the training drive, participants then completed the six minute experimental drives. If the participant was supposed to experience the no display condition first, the participant simply continued onto the next two baseline drives. After those two drives (each followed by the Within-Experiment Questionnaire), the participant took a five minute break, and then received the explanation for either the TOR or the reliability display. If the participant was supposed to experience either the TOR or the reliability display condition before the baseline drives, the participant received the explanation for the TOR or the reliability display prior to the first set of experimental drives. Then, after a five minute break, the participant completed the driving block of baseline drives.

At the end of the experiment, participants completed a Post-Experiment Questionnaire (Appendix I). This questionnaire consisted of the following 7 questionnaires: 1) a questionnaire assessing the perceived benefit of the display that the participant experienced, 2) a questionnaire assessing whether the participant was able perceive a difference between the two failure types, and whether they consciously were able to anticipate the failure events, 3) a questionnaire to assess driving history, 4) Driving Style Questionnaire (Stahl, 2015), 5) Manchester Driver Behavior Questionnaire (Lajunen, Parker, & Stradling, 1998), 6) Susceptibility to Distracted Driving Questionnaire (SDDQ) (Feng, Marulanda, & Donmez, 2014), 7) a basic demographic information questionnaire (e.g., income, education level, etc.).

At the end of the experiment, participants were compensated for their time.

Chapter 4

4 Measures

4.1 Driving measures for take-over quality

Takeover quality was assessed by focusing on hands-on-wheel behavior, takeover behavior, and lane keeping behavior.

- Hands-On-Wheel Behavior
  - Hands-On-Wheel Prior to Failure is a binary variable. This variable assesses whether drivers put their hand on the wheel before a failure or after a failure. If the participant put their hands on the wheel prior to the failure event, then they were prepared for the failure.
  - Hands-On-Wheel Time (s) was measured as when, relative to the failure, the driver puts their hands on the wheel to take over control. As participants were told to drive with their hands off the wheel when the LK was engaged, the steering wheel did not move until a participant put their hands on the wheel. Therefore, the Hands-On-Wheel Time was determined by the first movement of the steering wheel while the LK was engaged. Hands-on-wheel time is positive if the driver put their hands on the wheel before the failure and negative if they put their hands on the wheel after the failure. It should be noted that the automation was disengaged only after the driver moved the steering wheel for more than 5^o or they pressed the LK on/off button.
- Take Over Behavior – LK Off
  - Take-Over Prior to Failure is a binary variable. This variable assesses whether drivers took over vehicle control before a failure or after a failure, by either moving the steering wheel for more than 5 degrees or by pressing the LK on/off button.
  - Take-Over Time (s) was measured as when, relative to the failure, the driver turned off the LK by either moving the steering wheel for more than 5^o or by pressing the LK on/off button.
- Lane Keeping Behavior
  - Time Out of Lane (s) was calculated as the total amount of time that any part of the car was out of the lane during a failure event. If there were no lane departures, the value was set to 0. This variable could only be calculated for unpredictable failure events due to simulator limitations in recording the lane position data at intersections (used for predictable events).

- Standard Deviation of Lane Deviation (m) was defined as the standard deviation of how much the vehicle deviates from the lane center for the 20 seconds after the participants takes over control of the car during a failure event.

Take over quality was further assessed with an analysis of acceleration, steering wheel angle and steering wheel angle standard deviation profiles during the failure events. However, as mentioned earlier, as the predictable and unpredictable failures were created in different manners, the vehicle's behavior during each failure event may have been different, as the automation introduced different levels of accelerations for the different failures. Hence, even though the visual inspection showed the two failure types to be similar, the measurement of the following variables may not be comparable across the two failure types. Further research may be required to verify these variables.

- Maximum Acceleration After Takeover (m/s^2)
  - Maximum acceleration after takeover is defined as the maximum vehicle acceleration in the X-Y axis during a failure event, measured from the point where the participant takes over control from the vehicle. The measurement starts after the participant takes over control from the vehicle to exclude the accelerations caused by the failure event, and to only look at the takeover quality. The variable is calculated as follows:
    - $a_c = \sqrt{a_{long}^2 + a_{lat}^2}$
- Steering Wheel Angle Range (degrees)
  - The steering wheel angle range was calculated as the sum of the maximum angle to the left of center and the maximum angle to the right of center that the driver turned the steering wheel during a failure event.
- Max Steering Wheel Angle (degrees)
  - This variable was measured as the maximum angle that the driver moved the steering wheel, either left or right of center.
- Standard Deviation of Steering (degrees)
  - This variable is defined as the standard deviation of all the steering wheel angles during the 20 seconds after the participants takes over control of the car during a failure event (Knappe, Keinath, Bengler, & Meinecke, 2007). This metric is related to driver workload.

4.2 Secondary Task Interaction Variables

The following variables are used to assess a participant's rate of interaction with the secondary task at different points throughout an experimental drive.

- Interactions 30s Prior to Failure
    - This variable counts the number of times the participant interacted with the secondary task during time period of the 30 seconds prior to failure.
- Interactions 20s Subsequent to Failure
    - This variable counts the number of times the participant interacted with the secondary task during the time period of 20 seconds after failure.

4.3 Self-Reported Measures

While participants responded to Pre-, Within- and Post-Experiment questionnaires, only the results of the Within-Experiment questionnaire were analyzed and reported in this work. The variables from the Within-Experiment questionnaire are below:

- Workload
    - Using the NASA-TLX questionnaire (Hart & Staveland, 1988), a participant's perceived workload was measured. A participant's workload score ranges from 0 (lowest) to 100 (highest).
- Situation Awareness (SA)
    - SA is measured using the SART questionnaire (Taylor, 1990). Responses were collected using a 7-point Likert scale (1=low, 7=high) to understand the participants degree of perception experienced along three main components of SA—Demand, Supply and Understanding. The scales for each of the components were then combined to calculate the overall SA. The formula for this combination is: SA=Understanding – (Demand – Supply).
- Perceived Risk
    - This variable was measured using the questionnaire developed by (Tsimhoni et al., 2003). The risk questionnaire requested that drivers match the scenario they just drove to one of 10 driving situations (1= 'driving on an easy road with no traffic, pedestrians, or animals while perfectly alert', 10= 'driving with my eyes closed; A crash is bound to occur every time I do this').
- Usefulness
    - This variable was measured using the acceptance questionnaire developed by (Van Der Laan et al., 1997) . The response was collected on a 5-point Likert scale, ranging from 'strongly disagree' to 'strongly agree' with the middle response being 'neutral'. For analysis, the responses were coded from -2 (lowest) to +2 (highest).

- Satisfaction
  - This variable was also measured using the acceptance questionnaire developed by (Van Der Laan et al., 1997) . The response was collected on a 5-point Likert scale, ranging from ‘strongly disagree’ to ‘strongly agree’ with the middle response being ‘neutral’. For analysis, the responses were coded from -2 (lowest) to +2 (highest).
- Trust
  - This variable was measured using a modified version of the trust questionnaire developed by (Jian et al., 2000b). In order to simplify the questionnaire, questions relating to distrust of the system were eliminated, and a question regarding the participant’s comfort in engaging in the secondary task while the automation was on was added. Therefore, there were a total of seven questions in the questionnaire. Responses were collected on a 7-point Likert scale ranging from ‘not at all’ to ‘extremely’. The responses were summed and then divided by 7 such that a participant’s trust would be calculated to be out of 7.

Chapter 5

5 Analysis

5.1 Regression Models

The combination of the linear mixed models and a priori contrasts were used for variable analysis. As previously explained, due to the inherent differences between the second predictable failure and the rest of the failures that participants experienced in the experiment, only the first failures from each drive were used for the analysis (except where otherwise indicated).

5.1.1 Regression Models for Takeover Quality

Variables Hands-On-Wheel Time, Take-Over Time, Maximum Acceleration After Takeover, Steering Wheel Angle Range, Maximum Steering Wheel Angle, and Standard Deviation of Steering Wheel Angle were analyzed using mixed linear models through the SAS MIXED procedure, with display type, display present and failure type as fixed factors and participant as a random factor, and the compound symmetry variance-covariance structure. When the homogeneity of variance was not met, an unstructured variance covariance matrix was chosen. Observations where participants did not have the lane keeping on for at least 20s prior to a failure event, as well as observations where participants did not follow the directions, were removed from the analysis, and treated as missing data. Therefore, there were a total of 136 observations that were used in this analysis.

Variables Time Out Of Lane and Standard Deviation of Lane Deviation were also analyzed using mixed linear models through the SAS MIXED procedure in the same manner as described above, however, only display type and display present were the fixed factors as the data set for those variables only looked at unpredictable failures. Predictable failures were not observed because simulators do not record the lane center at intersections in a consistent manner. Observations where participants did not have the lane keeping on for at least 20s prior to a failure event were removed from the analysis, and therefore a total of 134 observations that were used in this analysis.

For the following four dependent measures, variance stabilizing transforms were not identified, and therefore, an unstructured variance/covariance matrix was used to create their linear models:

- Hands-On-Wheel Time (s)
- Take-Over Time (s)
- Standard Deviation of Steering Wheel Angle (degrees)
- Time Out Of Lane (s)

5.1.2 Regression Models for the Takeover Quality Binary Variables

Analysis of the binary variables for Hands-On-Wheel Time, Take-Over Time, and Time Out of Lane was performed using the SAS GENMOD procedure. A logistic regression was performed using a logit link function to understand the relationship between the display type and the failure type with whether a participant put their hands on the wheel prior to the failure, or whether a participant turned off the lane keeping prior to a failure, or whether a participant left the lane. Observations where participants did not have the lane keeping on for at least 20s prior to a failure event were removed from the analysis, and therefore a total of 136 observations that were used in this analysis for Hands-On-Wheel Time, and 134 observations were used for Time Out of Lane.

As the regression model did not converge using a three-way interaction term for the independent variables for the binary variable for Hands-On-Wheel Time, the logistic regression was only able to include the interactions between the display type and display present, and the interaction between display present and failure type

As the regression model with a three-way interaction for the independent variables also did not converge for the binary variable for Take-Over Time, the logistic regression was only able to include the interactions between display type and display present, and the interaction between display type and failure type. This lack of convergence may have been due to the lack of observations due to removing the second failure events from the analysis.

5.1.3 Regression Models for the Effect of Stage of Takeover on Takeover Quality

To understand the effect of the stage of takeover, which is whether a participant put their hands on the wheel prior to failure and whether a participant took over control of the automation prior to a failure, has on the takeover quality variables, covariate analysis was performed. The binary variables Hands-On-Wheel Prior to Failure and Take-Over Prior to Failure were each added separately to the linear models. This new linear models were created with the SAS MIXED procedure, and used display type, display present, failure type and Hands-On-Wheel Prior to Failure (or Take-Over Prior to Failure) as fixed factors and participant as a random factor. As the homogeneity of variance assumption was not met, an unstructured variance covariance matrix was chosen.

For the analysis of the take-over quality variables Time Out Of Lane and Standard Deviation of Lane Deviation, models were created with the SAS MIXED procedure, and used display type, display present and Hands-On-Wheel Prior to Failure (or Take-Over Prior to Failure) as fixed factors and participant as a random factor. As the homogeneity of variance assumption was not met, an unstructured variance covariance matrix was chosen.

5.1.4 Regression Models for the Rate of Interactions with the Secondary Task

Analysis of the rate of interactions with the secondary task at different time periods during the drive was performed using the SAS GENMOD procedure. A Poisson regression was performed using a log link function to understand if there was a relationship between the display type and the failure type with the number of interactions with the secondary task. Observations where participants did not have the lane keeping on for at least 20s prior to a failure event were removed from the analysis, as manual driving would impact a participant's use of the secondary task. Due to technical issues when transferring the data, there also were some missing observations. Therefore, a total of 131 observations were used in this analysis.

5.1.5 Regression Models for the Self-Reported Measures

Variables Workload, Perceived Risk, Situation Awareness, Usefulness, Satisfaction, and Trust were analyzed using mixed linear models through the SAS MIXED procedure, with display type, display present and failure type as fixed factors and participant as a random factor, and the compound symmetry variance-covariance structure. There were a total of 144 observations that were used in this analysis.

5.1.6 Regression Models for the Effect of Leaving the Lane on Takeover Quality

To understand the effect of leaving the lane on the takeover quality variables during unpredictable failures, covariate analysis was performed. This analysis only included unpredictable failures as the driver's Time Out of Lane could only be measured during unpredictable failure scenarios. As a participant leaving their lane is guaranteed to impact a driver's takeover quality, this analysis, and the results associated with it are located in Appendix K.

5.2 Contrasts

As described earlier, there were eight possible scenarios for each of the participants. Each of these scenarios is detailed in Table 5, and labeled with a letter. To further elaborate on the table, in scenario b, participants who were in the reliability display group had the reliability display present, and experienced a predictable failure event.

Each of the contrasts were set up using Table 5 for guidance. For example, in order to understand the impact of introducing a reliability display during an unpredictable failure, it is necessary to subtract c from d.

Table 5: A table showing each of the possible scenarios a participant could have experienced.

Reliability				TOR			
Predictable		Unpredictable		Predictable		Unpredictable	
No Display	Display Present	No Display	Display Present	No Display	Display Present	No Display	Display Present
a	b	c	d	e	f	g	h

Therefore, specific contrasts were set up as follows:

A) Effect of failure type on driver response during baseline drives (predictable versus unpredictable failures)

$$\frac{(a+e)-(c+g)}{2}$$

B) Effect of introducing TOR for predictable failures (TOR versus no display at predictable failures)

$$f-e$$

C) Effect of introducing TOR for unpredictable failures (TOR versus no display at unpredictable failures)

$$h-g$$

D) Difference in effectiveness of TOR when there are predictable failures versus unpredictable failures

$$(f-e)-(h-g)$$

E) Effect of introducing a reliability display for predictable failures (reliability display versus no display at predictable failures)

$$b-a$$

F) Effect of introducing a reliability display for unpredictable failures (reliability display versus no display at unpredictable failures)

$$d-c$$

G) Difference in effectiveness of a reliability display when there are predictable versus unpredictable failures

$$(b - a) - (d - c)$$

H) Difference in effectiveness of TOR versus reliability displays for predictable failures, comparing each to their baseline drive counterpart

$$(f - e) - (b - a)$$

I) Difference in effectiveness of TOR versus reliability displays for unpredictable failures, comparing each to their baseline drive counterpart

$$(h - g) - (d - c)$$

For the analysis of Take-Over Prior to Failure, given that the model was unable to control for the baseline drives as it did not converge with the 3 way interaction, hence the above contrasts B through I could not be used to control for the baseline effect. Therefore, contrasts J and K were created:

J) Difference between the TOR versus reliability displays for predictable failures when the displays are present

$$f - b$$

K) Difference between the TOR versus reliability displays for unpredictable failures when the displays are present

$$h - d$$

Chapter 6

6 Results

Each of the variables in Section 3 were analyzed in the method described above. However, only the variables with significant results are reported below.

6.1 Driving Performance Measures

6.1.1 Effect of failure type on takeover

When participants encountered predictable failures during the baseline (i.e. no display) drives, the drivers appeared to be more prepared for the failure events than when drivers encountered unpredictable failures, as indicated by the box plot for the Hands-On-Wheel Time (Figure 12). However, while participants did prepare for the impending predictable failure events, the boxplot for the Take-Over Time (Figure 13) indicates that when no display was present, regardless of the failure type, participants only took over control from the automation after the failure event occurred.

Further analysis on the participant's takeover quality was performed using contrast A. The results of this analysis are located in Table 6. As seen in Table 6, participants put their hands on the wheel on average 1.85s sooner during the predictable failure event than in the unpredictable failure event, as indicated by the decrease in Hands-On-Wheel Time. Further analysis using logistic regression showed that participants were more likely to put their hands on the wheel prior to a predictable failure than an unpredictable failure (OR=14.82, 95% CI: 1.54, 142.39, $\chi 2(1)=5.45$, p=.02). These results indicate that drivers were more prepared for the predictable failure events than the unpredictable failure events.

However, the standard deviation of the driver's steering was greater at predictable failure events than unpredictable failure events (Figure 14). On average, the Standard Deviation of Steering was .96 degrees greater for the predictable failure than the unpredictable one.

Table 6: Effect of failure type on takeover

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Time (s)	-1.85	t(34)=-5.32	<.0001	-2.55	-1.14
Standard deviation of steering (degrees)	0.96	t(26)=3.31	0.0027	0.36	1.55

Mean	**-1.29**	**-4.97**	**1.09**	**-5.26**	**-0.49**	**-3.28**	**0.50**	**-4.19**
S.D.	2.92	1.91	0.43	2.35	2.74	1.33	2.46	0.58

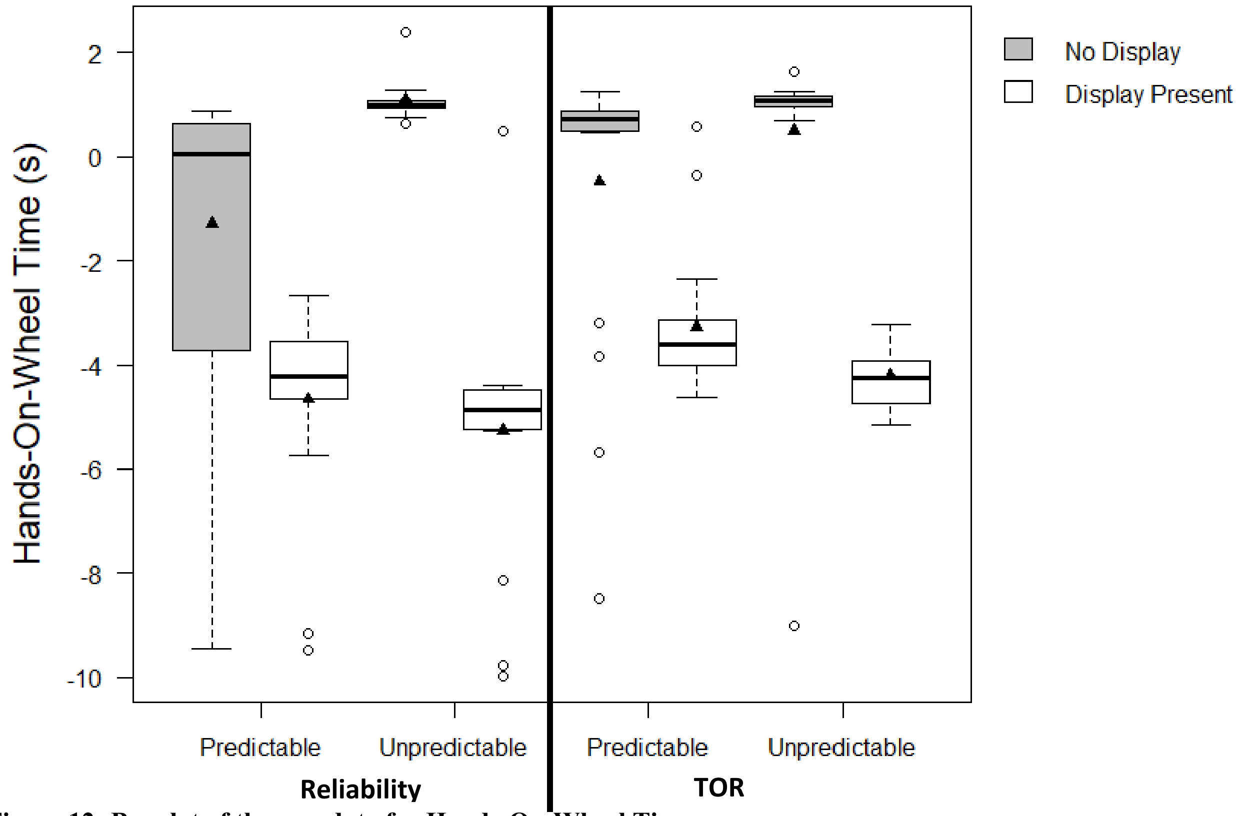

Figure 12: Boxplot of the raw data for Hands-On-Wheel Time

Mean	0.26	-3.02	1.22	-2.71	0.82	-.65	1.20	-0.56
S.D.	1.46	2.31	0.42	2.32	0.53	1.89	0.22	1.91

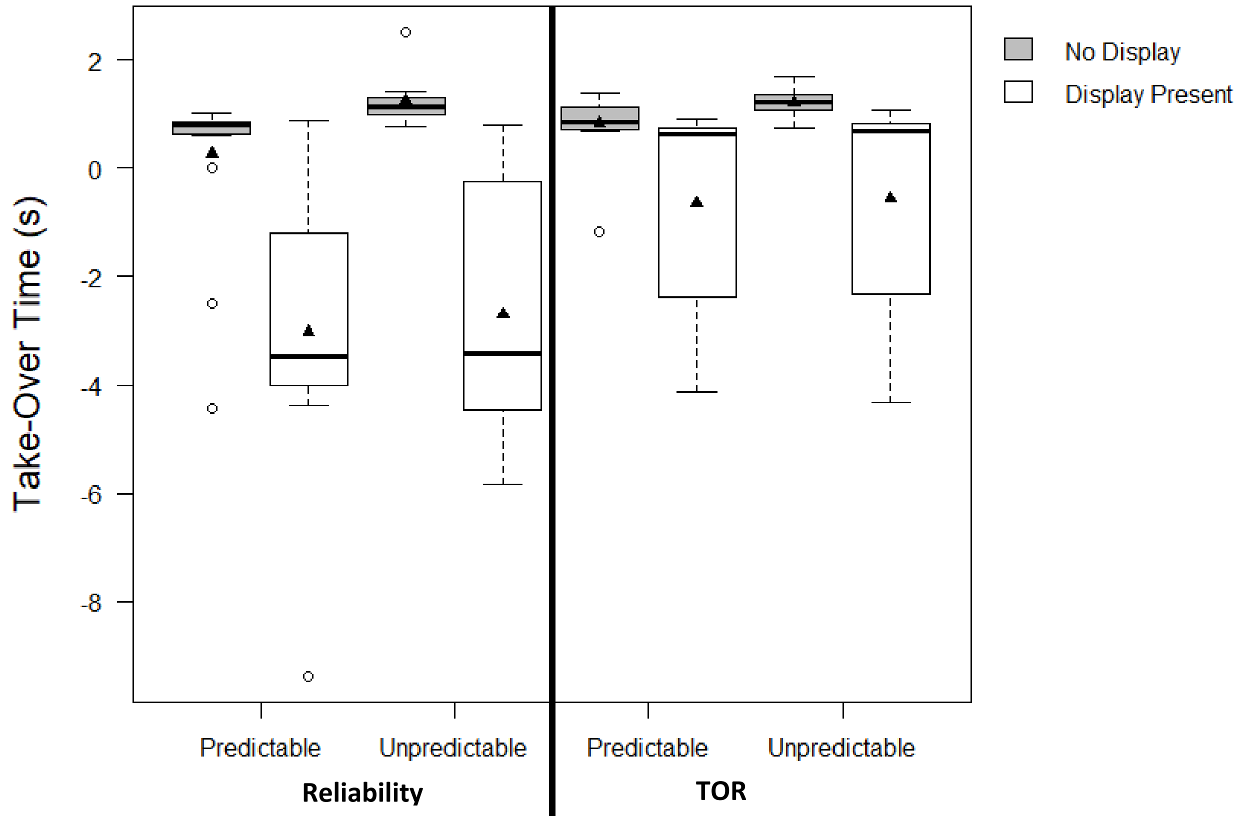

Figure 13: Boxplot of the raw data for Take-Over Time

Mean	**4.67**	**1.75**	**4.05**	**1.57**	**5.18**	**3.42**	**3.87**	**2.17**
S.D.	1.97	1.13	0.84	0.92	1.72	1.79	0.98	1.03

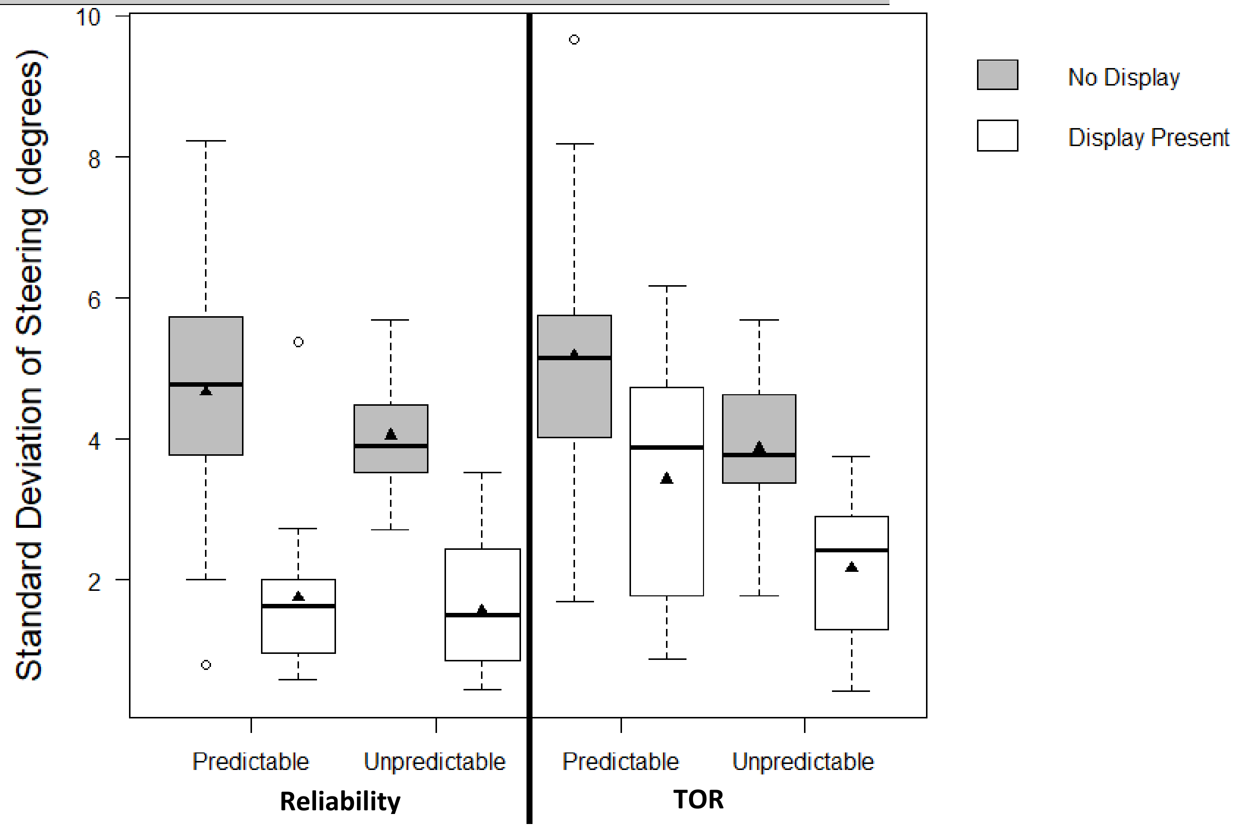

Figure 14: Boxplot of the raw data for the Standard Deviation of Steering Wheel Angle

6.1.2 Effect of introducing TOR (TOR versus no display)

The effect of introducing TOR is broken down into three areas: 1) the effect of introducing a TOR at predictable failure events, 2) the effect of introducing a TOR at unpredictable failure events, and 3) the difference in the effect of the introduction of a TOR at predictable failure events versus unpredictable failure events. The analysis below showed that the TOR has a positive effect on a driver's takeover quality, and drivers prepared for and responded to failure events sooner when there was a TOR present.

<u>Effect of introducing TOR on predictable failures</u>

As compared to the driving without a display present, when the TOR display was present, participants appeared to be more prepared for, and respond sooner to predictable failures, as indicated by the boxplots for the Hands-On-Wheel Time (Figure 12) and Take-Over Time (Figure 13). Furthermore, the quality of a participant's take-over also appears to show improvement when the TOR display was introduced at predictable failure events, as indicated by the boxplots for Maximum Acceleration After Takeover (Figure

15), Angle Range (Figure 16), Maximum Angle (Figure 17) and Standard Deviation of Steering (Figure 14), as each of these takeover quality measures appear to decrease when the TOR is present.

Further analysis was performed using contrast B. The results of this analysis are located in Table 7. When TOR is introduced, drivers put their hands on the wheel 2.4s sooner than when there is no TOR, as indicated by the Hands-On-Wheel Time. The odds ratio for a participant's Hands-On-Wheel Time was 111.41 ($\chi^2(1)=8.90$, $p=.003$, 95% CI: 5.04, 2464.73), which shows that participants were more likely to put their hands on the wheel prior to a predictable failure event when the TOR was present. In fact, 95% of the participants put their hands on the wheel prior to the failure event when the TOR was present at the predictable failure, as opposed to the 21% who put their hands on the wheel prior to the predictable failure event when there was no TOR display present (

Table 8). Participants also turned the lane keeping off 1.5s sooner on average with the TOR present than without the TOR present, as indicated by the Take-Over Time. Even though participants turned the lane keeping off sooner when the TOR display was present at predictable failure events, as shown in

Table 8, 37% of the participants took over control of the automation prior to the failure event when the TOR was present, while only 5% of the participants took over prior to the failure when there was no display present, which shows that even with the TOR, participants tended to wait until the failure started to occur to take over control of the driving task.

The driving quality was also significantly better when the TOR was present, as indicated by the average 1 m/s^2 decrease in Maximum Acceleration After Take-Over, the average Angle Range decrease of 7.8 degrees, the average Maximum Angle decrease of 7.7 degrees, and the average 1.7 degree decrease in the Standard Deviation of Steering.

Table 7: Effect of Introducing TOR for Predictable Failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Time (s)	-2.42	t(34)=-3.61	0.001	-3.79	-1.06
Take-Over Time (s)	-1.47	t(26)=-2.83	0.0089	-2.54	-0.4
Maximum Acceleration After Take-Over (m/s^2)	-0.97	t(26)=-3.9	0.0006	-1.48	-0.46
Angle Range (degrees)	-7.79	t(26)=-2.97	0.006	-13.17	-2.4
Maximum Angle (degrees)	-7.66	t(26)=-3.91	0.0006	-11.68	-3.63
Standard deviation of steering (degrees)	-1.75	t(26)=-4.69	<.0001	-2.52	-0.99

Table 8: Percentage of participants who prepared for, or took over prior to the predictable failure event

	No Display	TOR Present
Hands-On-Wheel Prior To Failure	21%	95%
Take-Over Prior To Failure	5%	37%

Mean	**2.53**	**0.89**	**2.61**	**0.95**	**2.8**	**1.83**	**2.53**	**1.34**
S.D.	1.42	0.66	0.67	0.56	1.26	1.07	0.76	0.69

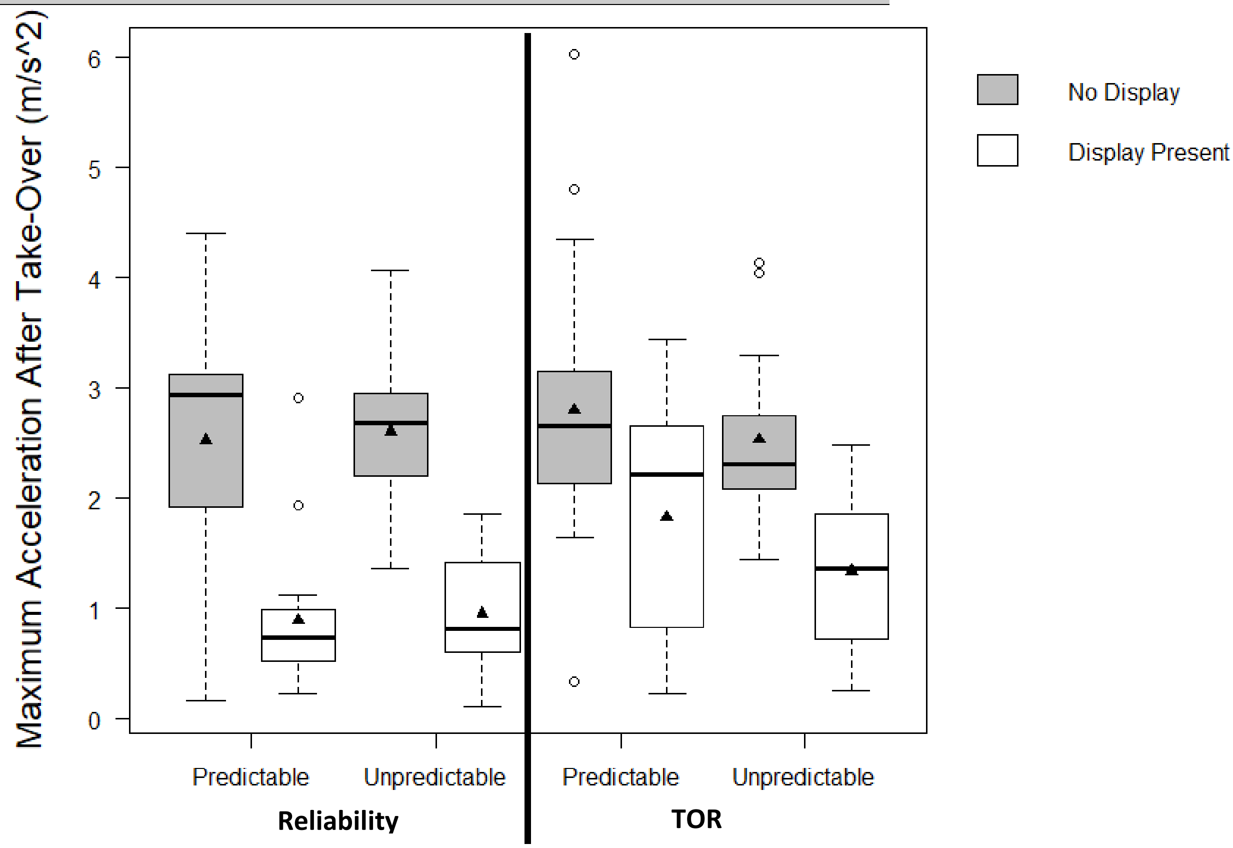

Figure 15: Boxplot of the raw data for the Maximum Acceleration After Take-Over

Mean	**26.67**	**10.43**	**26.40**	**7.41**	**27.88**	**20.09**	**25.2**	**12.57**
S.D.	13.82	5.74	8.24	5.53	12.90	9.96	9.15	8.14

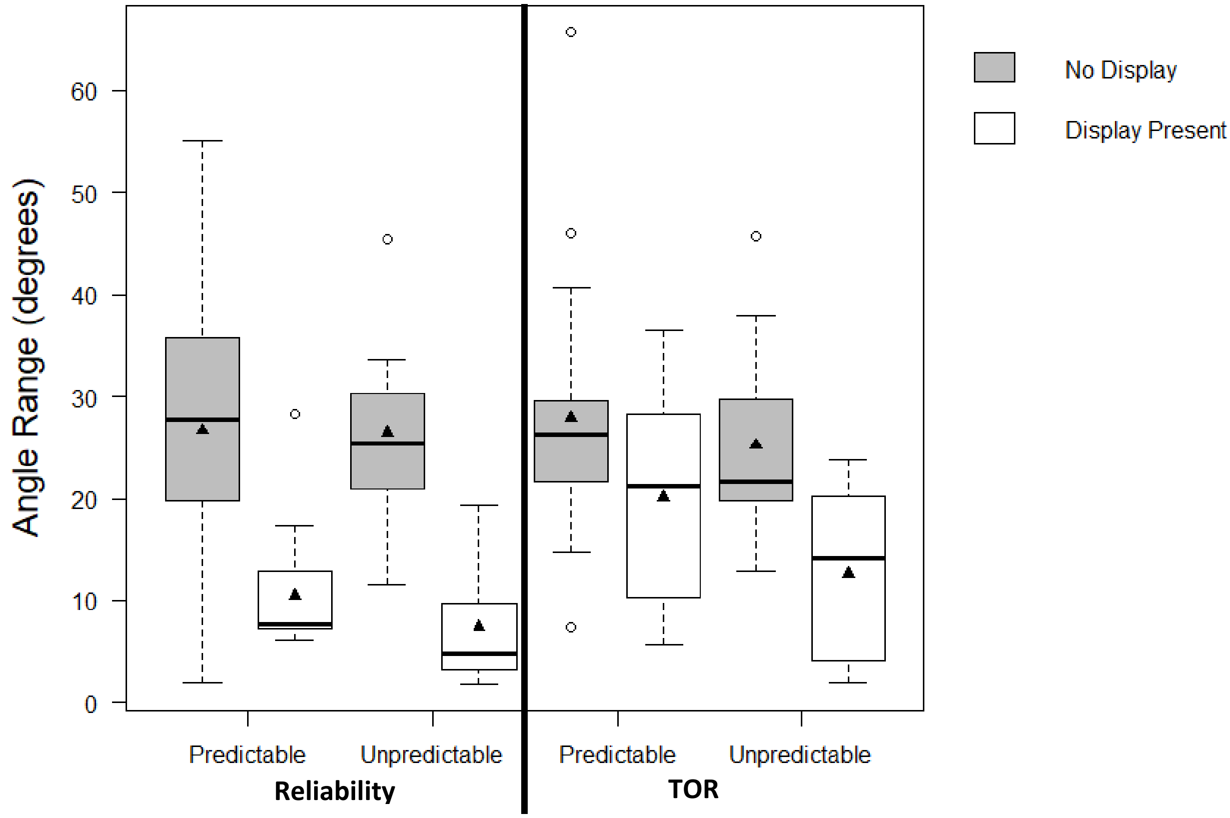

Figure 16: Boxplot of the raw data for the Angle Range

Mean	**18.43**	**8.47**	**19.00**	**5.10**	**20.64**	**12.99**	**19.00**	**8.21**
S.D.	9.13	3.78	5.72	3.47	10.69	6.18	7.44	5.44

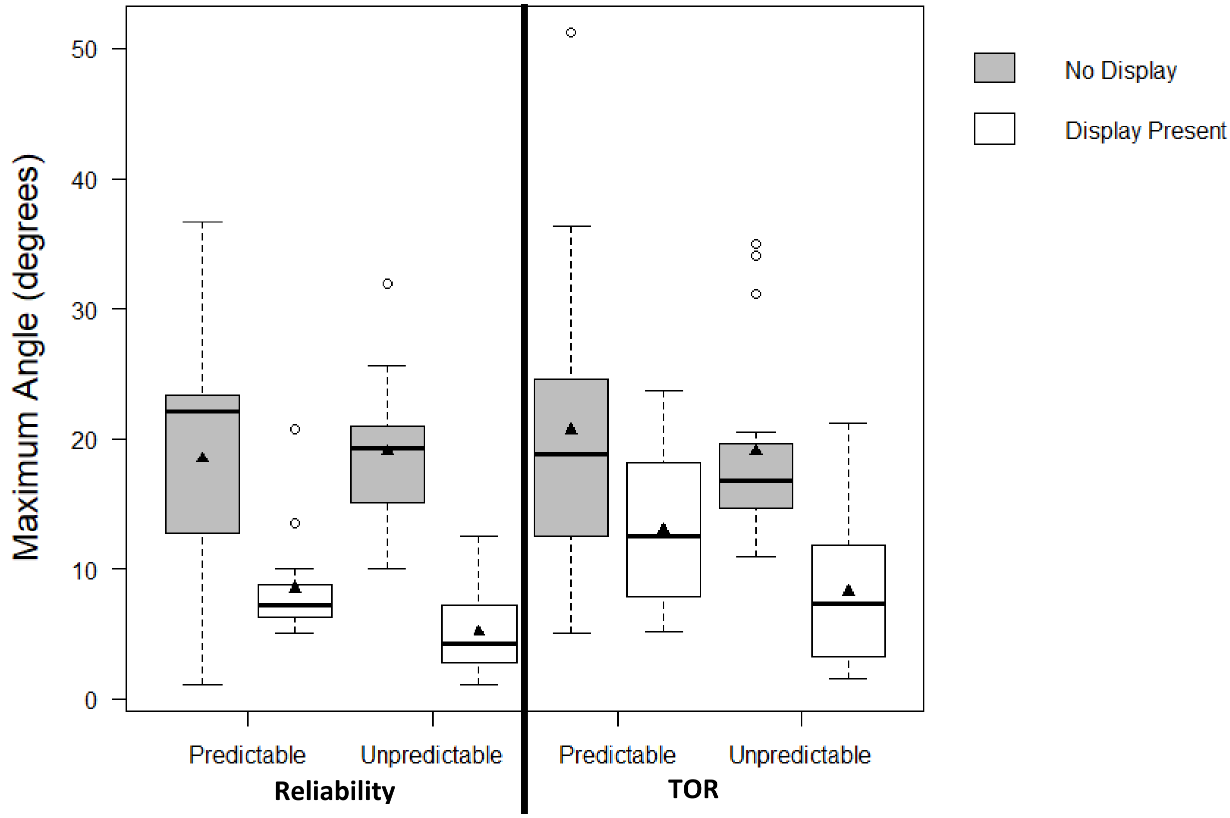

Figure 17: Boxplot of the raw data for Maximum Angle

<u>Effect of introducing TOR on unpredictable failures</u>

The TOR also appears to have a significant benefit when it is present at unpredictable failure events. As shown in the boxplots for Hands-On-Wheel Time (Figure 12), and Take-Over Time (Figure 13), participants appear to prepare for and respond to the unpredictable failure events sooner when the TOR display was present than when it was not present. The quality of a participant's takeover also appears to show improvement, as the Maximum Acceleration After Takeover (Figure 15), Angle Range (Figure 16), Maximum Angle (Figure 17), and Standard Deviation of Steering (Figure 14) each appear to decrease when the TOR is present. When looking at both unpredictable failure events, the quality of a participant's driving after the failure event also shows improvement, as the time that the participant is out of the lane decreases, and the participants appear to also drive closer to the lane center. These results are shown in the boxplots for Time Out of Lane (Figure 18), and the Standard Deviation of Lane Deviation (Figure 19).

Additional analysis was conducted using contrast C, and the results are located in Table 9. With the TOR display present at unpredictable failure events, participants put their hands on the wheel on average 5s sooner than when there was no display present, as indicated by the Hands-On-Wheel Time. The odds ratio for the Hands-On-Wheel Time is 1558.87[5] ($\chi^2(1)=27.01$, $p<.0001$, 95% CI: 97.46, 24934.19), indicating that when the TOR display was present, participants were significantly more likely to put their hands on the wheel prior to the unpredictable failure event. The odds ratio is very high here because when the TOR display was present, all of the participants put their hands on the wheel prior to the failure event, while only 6% of the participants put their hands on the wheel prior to the failure when no display was present (Table 11). Participants also turned off the lane keeping on average 1.8s sooner with the TOR, as indicated by the Take-Over Time. As shown in Table 11, none of the participants took over prior to the failure event when there was no display, however, when the display was present, 41% of participants took over prior to the unpredictable failure event.

Participants take-over quality was also significantly better with the TOR display present than when participants were driving in the baseline condition. When the TOR was present, the driver's Maximum Acceleration After Take-Over was 1.64 m/s^2 less than when there was no TOR, and the drivers moved the steering wheel on average 12.6 degrees less, as indicated by the Angle Range, and their Maximum Angle was 10.7 degrees less. Additionally, the Standard Deviation of the Steering was on average 1.7 degrees less with the TOR than the baseline condition, which shows that the drivers on average drove significantly better for the 20 subsequent to a failure with the TOR than the baseline condition. When both unpredictable failure events were analyzed together to further understand the impact of introducing TOR on a participant's takeover quality, the results show that on average, drivers were out of the lane for 1.6s less than when there was no display, as indicated by Time Out of Lane (Table 10). Additionally, the Standard Deviation of Lane Deviation was also decreased by .1 m on average when the TOR was present (Table 11). Each of these results show that participants maintained better control of the vehicle when there was a TOR present than when there was no TOR.

Table 9: Effect of Introducing TOR for Unpredictable Failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Time (s)	-4.98	t(34)=-9.28	<.0001	-6.07	-3.89
Take-Over Time (s)	-1.76	t(26)=-3.20	0.0036	-2.89	-0.63
Maximum Acceleration After Take-Over (m/s^2)	-1.64	t(26)=-6.22	<.0001	-2.18	-1.1
Angle Range (degrees)	-12.6	t(26)=-4.5	0.0001	-18.36	-6.84
Maximum Angle (degrees)	-10.69	t(26)=-5.12	<.0001	-14.99	-6.4
Standard deviation of steering (degrees)	-1.68	t(26)=-4.2	0.0003	-2.5	-0.86

[5] The odds ratio is very high here because there were no participants who put their hands on the wheel after the failure event when the TOR display present, see Table 11.

Table 10: Effect of Introducing TOR for Unpredictable Failure on Lane Departure

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Time Out of Lane (s)	-1.59	t(34)=-5.06	<.0001	-2.22	-0.95
Standard Deviation of Lane Deviation (m)	-0.1	t(34)=-4.26	0.0002	-0.15	-0.05

Table 11: Percentage of participants who prepared for, or took over prior to the unpredictable failure event

	No Display	TOR Present
Hands-On-Wheel Prior To Failure	6%	100%
Take-Over Prior To Failure	0%	41%

Mean	**1.95**	**0.26**	**2.56**	**0.75**
S.D.	1.42	0.58	2.01	0.9

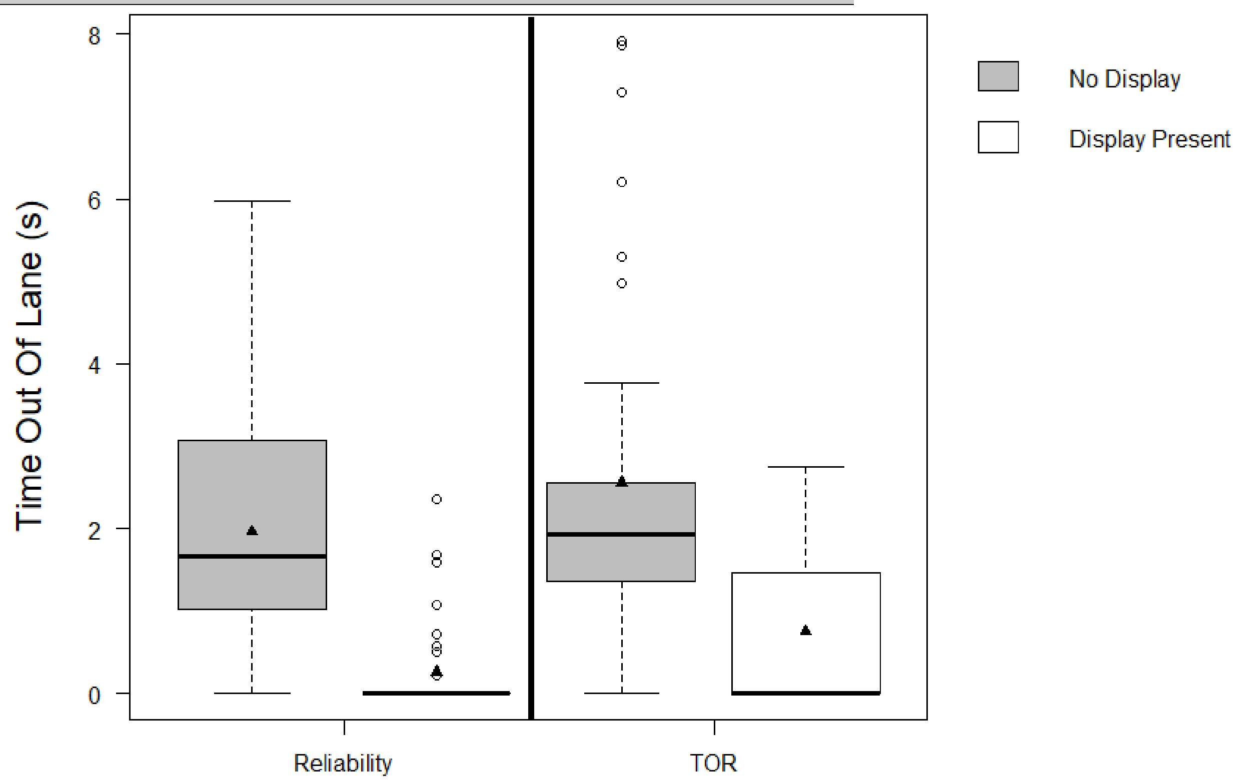

Figure 18: Boxplot of the raw data for Time Out of Lane

Mean	0.41	0.23	0.36	0.28
S.D.	0.18	0.11	0.11	0.13

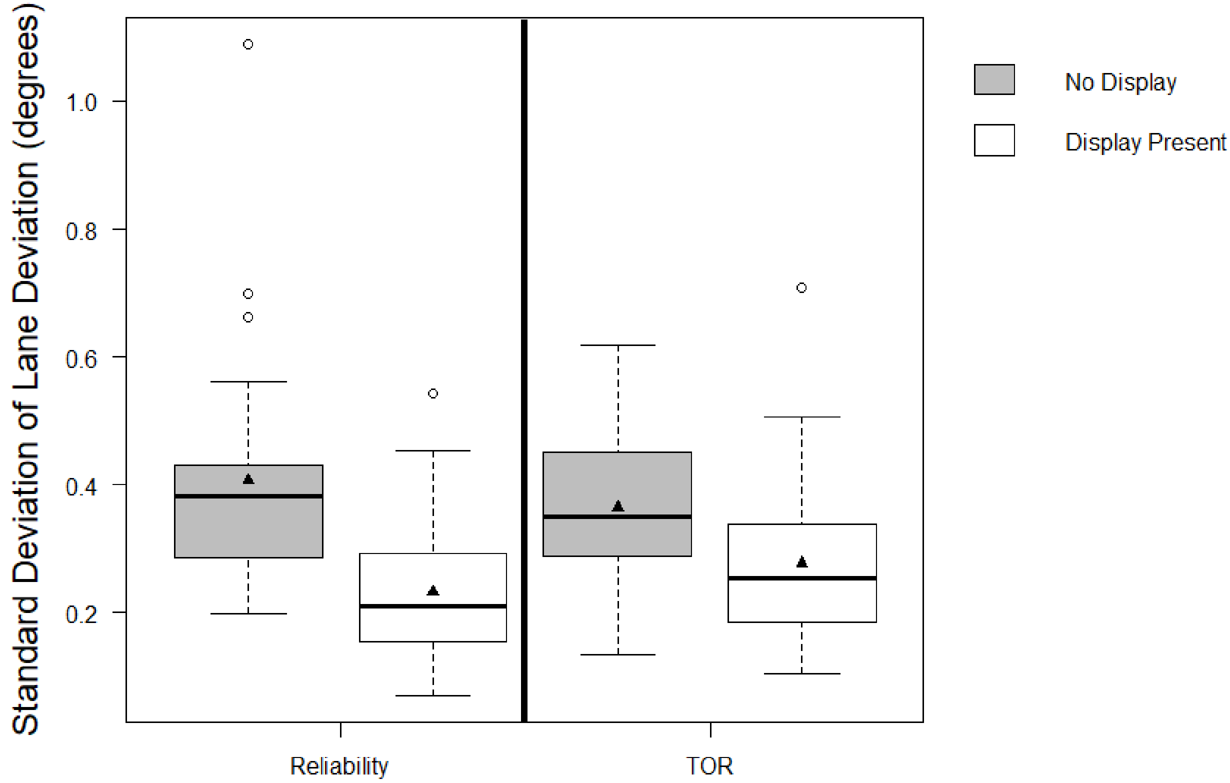

Figure 19: Boxplot of the raw data for the Standard Deviation of Lane Deviation

<u>Difference in the effect of introducing TOR for predictable and unpredictable failures</u>

As the effect of introducing TOR is not immediately clear using the boxplots, it is necessary to conduct further analysis using contrast D. The results of this analysis are in Table 12. While most of the measures are not significant, there is, however, a significant difference between the Hands-On-Wheel Time for the predictable failures and the unpredictable failures. On average, participants put their hands on the wheel 2.5s later when they experienced a predictable failure event versus an unpredictable failure event.

Table 12: Difference in effectiveness of TOR when there is a predictable failure versus an unpredictable failure

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Time (s)	2.55	t(34)=3.43	0.0016	1.04	4.08

6.1.3 Effect of introducing a reliability display (reliability display versus no display)

The effect of introducing the reliability display is broken down into three areas: 1) the effect of introducing a reliability display at predictable failure events, 2) the effect of introducing a reliability display at unpredictable failure events, and 3) the difference in the effect of the introduction of a reliability display at predictable failure events versus unpredictable failure events. The analysis below showed that the reliability display has a positive effect on a driver's takeover quality, and drivers prepared for and responded to failure events sooner when there was a reliability display present.

Effect of introducing a reliability display at predictable failures

The reliability display appears to have a significant benefit when it is present at predictable failure events. As shown in the boxplots for Hands-On-Wheel Time (Figure 12), and Take-Over Time (Figure 13), participants appear to prepare for and respond to the predictable failure events sooner when the reliability display was present than when it was not present. The quality of a participant's takeover also appears to show improvement, as the Maximum Acceleration After Takeover (Figure 15), Angle Range (Figure 16), Maximum Angle (Figure 17), and Standard Deviation of Steering (Figure 14) each appear to decrease when the reliability display is present.

Further analysis was performed using contrast E. The results are in Table 13. On average, drivers put their hands on the wheel 3.66s sooner when there was a reliability display than when there was not, as indicated by the Hands-On-Wheel Time. Logistic regression showed that participants were more likely to put their hands on the wheel prior to a predictable failure event when the display was present (OR=44.47, $\chi^2(1)=22.63$, $p<.0001$, 95% CI: 9.31, 212.33), in fact, when the display was present, all of the participants in the reliability display condition put their hands on the wheel prior to the failure event, while when there was no display present, only 47% of the participants put their hands on the wheel prior to the failure event (Table 14). Additionally, participants turned off the lane keeping 3.3 sooner, on average, as indicated by the Take-Over Time (Table 13), and 94% of the participants in the reliability display condition turned off the lane keeping prior to the failure event when the reliability display was present (Table 14). The driver's takeover quality when a reliability display was present was significantly better than when the reliability display was not present. On average, the Maximum Acceleration After Take-Over was decreased by 1.64 m/s^2, the Angle Range was decreased by 16.24 degrees, the Maximum Angle was decreased by 10 degrees, and the Standard Deviation of Steering was decreased by 2.9 degrees.

Table 13: Effect of introducing a reliability display on predictable failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Time (s)	-3.66	t(34)=-5.11	<.0001	-5.12	-2.21
Take-Over Time (s)	-3.28	t(26)=-5.95	<.0001	-4.41	-2.14
Maximum Acceleration After Take-Over (m/s^2)	-1.64	t(26)=-6.22	<.0001	-2.18	-1.1
Angle Range (degrees)	-16.24	t(26)=-5.86	<.0001	-21.93	-10.55
Maximum Angle (degrees)	-9.96	t(26)=-4.82	<.0001	-14.22	-5.71
Standard deviation of steering (degrees)	-2.92	t(26)=-7.39	<.0001	-3.73	-2.11

Table 14: Percentage of participants who prepared for, or took over prior to the predictable failure event

	No Display	Reliability Present
Hands-On-Wheel Prior To Failure	47%	100%
Take-Over Prior To Failure	18%	94%

Effect of introducing a reliability display at unpredictable failures

The reliability display also appears to have a significant benefit when it is present at unpredictable failure events. As shown in the boxplots for Hands-On-Wheel Time (Figure 12), and Take-Over Time (Figure 13), participants appear to prepare for and respond to the unpredictable failure events sooner when the reliability display was present than when it was not present. The quality of a participant's takeover also appears to show improvement, as the Maximum Acceleration After Takeover (Figure 15), Angle Range (Figure 16), Maximum Angle (Figure 17), and Standard Deviation of Steering (Figure 14) each appear to decrease when the reliability display is present. When looking at both unpredictable failure events, the quality of a participant's driving after the failure event also shows improvement, as the time that the participant is out of the lane decreases, and the participants appear to also drive closer to the lane center. These results are shown in the boxplots for Time Out of Lane (Figure 18), and the Standard Deviation of Lane Deviation (Figure 19).

Further analysis was conducted using contrast F. The results of this analysis are in Table 15. On average, drivers put their hands on the wheel 6.3s sooner when there was a reliability display than when there was not, as indicated by the Hands-On-Wheel Time. Drivers were also more likely to put their hands on the wheel prior to a failure event when the reliability display was present than when there was no display present (OR=622.19, $\chi^2(1)=13.1$, p=.0003, 95% CI: 18.98, 20392.58). The odds ratio is high here because when the reliability display was present, 94% of the participants put their hands on the wheel prior to the failure, while when there was no display present none of the participants put their hands on the wheel prior to the failure event (Table 17). Drivers also turned the lane keeping off on average 3.9s sooner when there was a reliability display, as indicated by the Take-Over Time. In fact, as seen in Table 17, 82% of the participants took over prior to the failure event when the reliability display was present, as opposed to the 0% who took over when there was no display present.

The Maximum Acceleration After Take-Over was on average 1.66 m/s^2 less with the reliability display, which indicates better vehicle control. Additionally, the Angle Range was on average 19 degrees less with the reliability display present, and the Maximum Angle was on average 14 degrees less with the reliability display, which indicates that drivers did not have to correct their driving nearly as much to get back into the center of the lane when a reliability display was present. The Standard Deviation of Steering was on average 2.5 degrees less when there was a reliability display present, which indicates that the driver's effort significantly decreased when the reliability display was present, and their driving quality improved.

When both unpredictable failures are analyzed, drivers appear to keep to their lanes significantly better. These results show that drivers had better control of the vehicle after the failure event when there was a reliability display present versus when there was no reliability display present. These results are presented in Table 16. When a reliability display was present, on average, the Time Out of Lane was decreased by 1.63s, and the Standard Deviation of Lane Deviation was decreased by on average .15 m.

Table 15: Effect of introducing a reliability display on unpredictable failures

	Estimate	t-Value	p-Value	Lower	Upper
Hands-On-Wheel Time (s)	-6.27	t(34)=-11.20	<.0001	-7.41	-5.13
Take-Over Time (s)	-3.92	t(34)=-6.62	<.0001	-5.14	-2.70
Maximum Acceleration After Take-Over (m/s^2)	-1.66	t(26)=-5.81	<.0001	-2.25	-1.09
Angle Range (degrees)	-19.21	t(26)=-6.38	<.0001	-25.4	-13.02
Maximum Angle (degrees)	-14.11	t(26)=-6.28	<.0001	-18.73	-9.49
Standard deviation of steering (degrees)	-2.48	t(26)=-5.78	<.0001	-3.37	-1.6

Table 16: Effect of introducing a reliability display for unpredictable failures on Lane Departure

	Estimate	t-Value	p-Value	Lower	Upper
Time Out of Lane (s)	-1.63	t(34)=-4.78	<.0001	-2.32	-0.93
Standard Deviation of Lane Deviation (m)	-0.15	t(34)=-5.79	<.0001	-0.21	-0.1

Table 17: Percentage of participants who prepared for, or took over prior to the unpredictable failure events

	No Display	Reliability Present
Hands-On-Wheel Prior To Failure	0%	94%
Take-Over Prior To Failure	0%	82%

<u>Difference in the effect of introducing a reliability display for predictable and unpredictable failures</u>

The difference in the effect of the introduction of a reliability display at predictable and unpredictable failures is not immediately clear when looking at the boxplots. Therefore, further analysis was conducted using contrast G, and the results are located in Table 18.

While most of the measures are not significant, the Hands-On-Wheel Time was on average 2.6s greater when experiencing a predictable failure versus an unpredictable failure.

Table 18: Difference in effectiveness of the reliability display when there is a predictable failure versus an unpredictable failure

	Estimate	t-Value	p-Value	Lower	Upper
Hands-On-Wheel Time (s)	2.6	t(34)=3.49	0.0013	1.09	4.12

6.1.4 Difference between the TOR and the reliability displays

While it is clear that the introduction of both the reliability display and the TOR had a positive impact on a driver's takeover time and takeover quality, it is necessary to compare the benefits of the two displays. Analysis of the differences between the TOR and reliability displays is broken down into two components: 1) the difference between the TOR and the reliability display at predictable failure events and 2) the difference between the TOR and reliability displays at unpredictable failure events. The analysis indicates that participants took over control of the automation sooner and had a better takeover quality when the reliability display was introduced, than when the TOR was introduced.

<u>Difference between the TOR and reliability displays for predictable failures</u>

An inspection of the boxplots shows that when the reliability display was introduced at predictable failures, participants took over sooner from the automation than when the TOR was introduced, as indicated by the Take-Over Time (Figure 13). Participants also appear to have a lower Maximum Acceleration After Takeover, Angle Range and Standard Deviation of Steering (Figure 15, Figure 16, and Figure 14) when the reliability display is introduced than when the TOR is introduced at predictable failure events. These boxplots appear to indicate that the reliability display improved participant's takeover time and quality.

Further analysis was performed using contrast H, and the results of this analysis are in Table 19. When the reliability display was introduced, participants Take-Over Time was on average 1.8s faster than when the TOR was introduced at a predictable failure. This may be because participants had more time to decide when to takeover, as the vehicle's reliability decreased before it reached its threshold. To further understand the difference between the reliability display and the TOR on a participant's Take-Over Time, contrast J was used in conjunction with logistic regression. This result provided an odds ratio of 39.81 ($\chi^2(1)=7.74$, $p=.0054$, 95% CI: 2.97, 533.52), which showed that participants were significantly more likely to take over control of the lane keeping prior to a predictable failure event when the reliability display was present than when the TOR was present.

Additionally, when a reliability display introduced, the Angle Range also was on average 8.5 degrees less for the reliability display, and the Standard Deviation of Steering was on average 1 degree less for the reliability display than for the TOR at the predictable failures.

These results show that at the predictable failures, participants had a smoother takeover when the reliability display was present versus when the TOR display was present. Drivers appear to be more prepared for the impending failure when the reliability display provides them with continuous updates on the automation's reliability versus the singular time the TOR appears 6s prior to a failure event.

Table 19: Difference between introducing TOR and Reliability displays for predictable failures

	Estimate	t-Value	p-Value	Lower	Upper
Take-Over Time (s)	1.80	t(26)=2.38	0.025	0.25	3.36
Angle Range (degrees)	8.46	t(26)=2.22	0.036	0.62	16.29
Standard deviation of steering (degrees)	1.17	t(26)=2.14	0.04	0.05	2.28

Difference between the TOR and reliability displays for unpredictable failures

A visual inspection of the boxplots shows that participants took over from the automation sooner when the reliability display was introduced, than when the TOR was introduced, as shown in the boxplot for Take-Over Time (Figure 13). Participants also appear to have a smaller Maximum Acceleration After Takeover when the reliability display was introduced than when the TOR was introduced (Figure 15).

Additional analysis was performed using contrast I, and the results are recorded in Table 20. The Take-Over Time is on average 2.2s longer when the TOR is introduced than when the reliability display is introduced. To further understand the difference between the reliability display and the TOR on a participant's Take-Over Time, contrast K was used in conjunction with logistic regression. This result provided an odds ratio of 6.49 ($\chi^2(1)=5.89$, $p=.015$, 95% CI: 1.43, 29.36), which showed that participants were significantly less likely to take over control of the lane keeping prior to an unpredictable failure event when the TOR was present than when the reliability display was present.

These results indicate that it is likely that when the drivers were provided with constant information about the reliability of the automation, they would takeover sooner, possibly before the failure. Drivers likely were more prepared for a possible failure event when there was a reliability display than when there was a TOR, and therefore had a better takeover quality, as indicated by the Maximum Acceleration After Takeover.

Table 20: Difference between introducing TOR and reliability displays for unpredictable failures

	Estimate	t-Value	p-Value	Lower	Upper
Take-Over Time (s)	2.16	t(26)=2.67	0.013	0.50	3.82

6.1.5 Effect of Stage of Takeover on Takeover Quality

A covariate analysis was conducted to investigate the effect of the stage of takeover on the participants' takeover quality. The stage of takeover is divided into two parts, either before the failure event, or after the failure event. Therefore, two variables are used for this analysis—the variable Hands-On-Wheel Time, which shows whether a participant prepared in advance for a failure event, and the variable Take-Over Time, which indicates participants' response time to a failure event. While these variables are significant in much of the above analysis, it is necessary to understand how preparing and responding to an impending failure prior to the event impact participants' takeover quality. The results below show that there is a significant improvement in takeover quality when participants prepare for the failure events prior to the failure, and when they takeover prior to the failure event.

As shown in Table 21, the Maximum Acceleration After Failure was significantly decreased when participants put their hands on the wheel prior to failure, and when they took over prior to the failure. The Maximum Acceleration After Failure decreased by .8 m/s2 on average when participants put their hands on the wheel prior to failure, as indicated by Hands-On-Wheel Prior to Failure. On average, the Maximum Acceleration After Failure decreased by 1.4 m/s2 when participants took over control from the automation prior to failure, as indicated by Take-Over Prior to Failure.

Table 21: Effect of stage of takeover on Maximum Acceleration After Failure

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Prior to Failure	-0.84	t(34)=-3.70	0.0008	-1.31	-0.38
Take-Over Prior to Failure	-1.42	t(34)=-12.02	<.0001	-1.66	-1.18

Additionally, there was a significant decrease in the Angle Range when the participant placed their hands on the wheel prior to failure, and turned off the automation prior to failure, as shown in Table 22. On average, Hands-On-Wheel Prior to Failure led to a decrease of 10.7 degrees in the Angle Range, and Take-Over Prior to Failure led to a decrease of nearly 14 degrees in the Angle Range.

Table 22: Effect of stage of takeover on Angle Range

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Prior to Failure	-10.67	t(34)=-4.24	0.0002	-15.79	-5.56
Take-Over Prior to Failure	-14.05	t(34)=-16.68	<.0001	-15.76	-12.34

As shown in Table 23, there was a significant decrease in the Maximum Angle when a participant put their hands on the wheel prior to failure, and when they took over control of the automation prior to failure. On average, when participants put their hands on the wheel prior to the failure, the Maximum Angle decreased by 8.2 degrees, as indicated by Hands-On-Wheel Prior to Failure. Take-Over Prior to Failure led to an average decrease in the Maximum Angle of 8.7 degrees.

Table 23: Effect of stage of takeover on Max Angle

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Prior to Failure	-8.24	t(34)=-4.78	<.0001	-11.75	-4.74
Take-Over Prior to Failure	-8.72	t(34)=-12.42	<.0001	-10.14	-7.29

As shown in Table 24, there also was a significant decrease in the Standard Deviation of Steering when participants put their hands on the wheel prior to failure, and when participants put their hands on the wheel prior to failure. On average, the Standard Deviation of Steering decreased by 1.6 degrees when participants put their hands on the wheel prior to the failure, as indicated by Hands-On-Wheel Prior to Failure. Additionally, the Standard Deviation of Steering decreased by an average of 2.2 degrees when participants took over control of the automation prior to failure, as indicated by Take-Over Prior to Failure.

Table 24: Effect of stage of takeover on Standard Deviation of Steering

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Prior to Failure	-1.55	t(34)=-4.58	<.0001	-2.23	-0.86
Take-Over Prior to Failure	-2.18	t(34)=-10.55	<.0001	-2.61	-1.76

As shown in Table 25, there was a significant decrease of an average .5s in the Time Out of Lane when participants took over prior to the failure.

Table 25: Effect of stage of takeover on the Time Out of Lane

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Take-Over Prior to Failure	-0.51	t(34)=-2.7	0.01	-0.9	-0.13

As shown in Table 26, there was a significant average decrease of .12 m in the Standard Deviation of Lane Deviation when a participant put their hands on the wheel prior to failure, as indicated by Hands-On-Wheel Prior to Failure. There also was a significant decrease of an average .08m in the Standard Deviation of Lane Deviation when participants took over control of the vehicle prior to the failure.

Table 26: Effect of stage of takeover on the Standard Deviation of Lane Deviation

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Hands-On-Wheel Prior to Failure	-0.12	t(34)=-2.05	0.048	-0.24	-0.0009
Take-Over Prior to Failure	-0.08	t(34)=-3.22	0.0029	-0.13	-0.03

6.2 Secondary Task Interaction Analysis

6.2.1 Effect of Failure Type on the Rate of Interactions

When participants encountered predictable failure events during the baseline drives, drivers seem to interact with the secondary task less often during the 30 second time period prior to the failure event than when participants encountered unpredictable failure events, as indicated by the boxplot for Interactions 30s Before Failure (Figure 20).

Additional analysis was conducted using contrast A, and the results of this analysis are in Table 27. These results show a 36% decrease in the rate of interactions with the secondary task 30s before the failure when the participant was at a predictable failure than when the participant was at an unpredictable failure during the baseline condition, as indicated by Interactions 30s Before Failure. It is therefore likely that participants were more aware of the impending failure events at the predictable failures than the unpredictable failures, and decreased their rate of interaction in order to prepare for the takeover. This result correlates to the results in section 3.6.3.1, which shows that the participants prepared for and responded to the predictable failure events sooner than the unpredictable failure events.

Table 27: Effect of Failure Type on the Rate of Interactions

	Estimate	Chi-Square	p-value	95% CI: Lower	95% CI: Upper
Interactions 30s Before Failure	0.64	$\chi^2(1)=26.08$	<.0001	0.54	0.76

Mean	**7.53**	**5.94**	**12.82**	**7.71**	**8.89**	**8.89**	**12.88**	**9.50**
S.D.	4.12	2.68	3.82	3.82	4.70	2.63	6.64	1.97

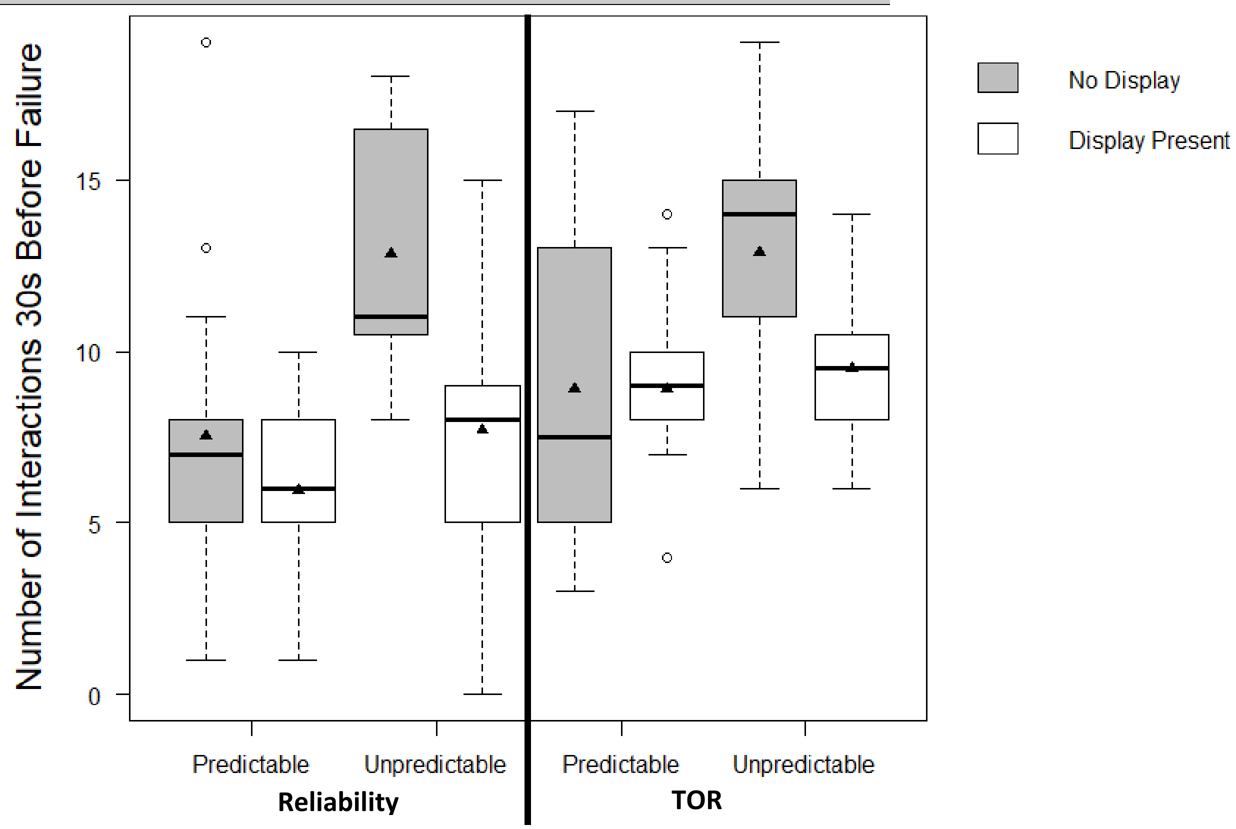

Figure 20: Boxplot of the raw data for the number of Interactions 30s Before Failure

6.2.2 Effect of introducing a TOR (TOR versus no display) on the rate of interactions

The analysis below indicates that when the TOR is introduced, participants interact with the secondary task less. This effect is significant at the unpredictable failure events.

Effect of introducing a TOR at predictable failures on the rate of interactions

There is no significant effect on the secondary task when the TOR is introduced at predictable failure events.

Effect of introducing a TOR at unpredictable failures on the rate of interactions

When the TOR was introduced at unpredictable failures, drivers appear to interact with the secondary task less during the 30s prior to a failure event when the TOR display is present than when the TOR display is not present. This relationship is clear in the boxplot for Interactions 30s Before Failure (Figure 20).

Further analysis was performed using contrast C. The results of this analysis are in Table 28. The results show that there was a 26% decrease in the rate of interactions with the secondary task 30s before the failure event, as indicated by Interactions 30s Before Failure. It is likely, therefore, that when participants were notified with the TOR that there would be an impending failure, they immediately decreased their use of the secondary task as they were not sure about when the failure would occur, and looked at the road.

Table 28: Effect of introducing a TOR at unpredictable failures

	Estimate	Chi-Square	p-value	95% CI: Lower	95% CI: Upper
Interactions 30s Before Failure	0.74	x2=35.15	<.0001	0.67	0.82

Difference in the effect of introducing a TOR at predictable versus unpredictable failures on the rate of interactions

When the effect of the introduction of TOR was compared between predictable and unpredictable failures, participants interacted more with the secondary task 30s prior to the failure event at predictable failures than unpredictable failure events (Figure 20).

This result is confirmed using contrast D (see Table 29). The results show that the rate of Interactions 30s Before Failure increased by 36% when the TOR was introduced at predictable failures versus when it was introduced at unpredictable failures.

Table 29: Difference in effect of introducing TOR for predictable versus unpredictable failures

	Estimate	Chi-Square	p-value	95% CI: Lower	95% CI: Upper
Interactions 30s Before Failure	1.36	$\chi^2(1)=6.19$	0.01	1.07	1.73

6.2.3 Effect of introducing a reliability display (reliability display versus no display) on the rate of interactions

When the reliability display was introduced, participants interacted less with the secondary task at unpredictable failure events.

Effect of introducing a reliability display at predictable failures on the rate of interactions

There is no significant effect on the secondary task when the reliability display is introduced at predictable failure events.

Effect of introducing a reliability display at unpredictable failures on the rate of interactions

When the reliability display is introduced at unpredictable failures, participants appear to decrease their rate of interactions during the time period of 30s prior to failure. This relationship is clearly shown in the boxplot for Interactions 30s Before Failure (Figure 20).

Additional analysis was conducted using contrast F. The results of this analysis are in Table 30. The results show a 40% decrease in the rate of interaction during the time period of 30s prior to a failure when a reliability display is present at the unpredictable failures.

Table 30: Effect of introducing a reliability display at unpredictable failures

	Estimate	Chi-Square	p-value	95% CI: Lower	95% CI: Upper
Interactions 30s Before Failure	0.6	$\chi^2(1)=27.53$	<.0001	0.5	0.73

Difference in effect of introducing a reliability display at predictable versus unpredictable failures on the rate of interactions

There is no significant difference in the rate of interactions when the reliability display is introduced at predictable failures or unpredictable failures.

6.2.4 Difference between the Effects of TOR and Reliability displays on the rate of interactions

There is no significant difference between the rates of interaction with the secondary task when the TOR was introduced or when the reliability display was introduced.

6.3 Self-Reported Measures Analysis

6.3.1 Effect of failure type on takeover

A visual inspection of the self-reported data does not show a significant effect of failure type on takeover. Additional analysis performed with contrast A showed that there were no significant results for any of the self-reported measures when looking at the effect of failure type on failure type.

6.3.2 Effect of Introducing TOR (TOR versus no display)

The effect of introducing TOR is broken down into three areas: 1) the effect of introducing a TOR at predictable failure events, 2) the effect of introducing a TOR at unpredictable failure events, and 3) the difference in the effect of the introduction of a TOR at predictable failure events versus unpredictable failure events. The analysis below showed that the introduction of TOR has a positive effect on the driver's workload, situation awareness and trust at predictable failures, and had a positive effect on the driver's trust at unpredictable failure events.

Effect of Introducing TOR at predictable failures

When the TOR was introduced at predictable failure events, participants appear to have a lower perceived workload, an increased situation awareness and an increase in system trust. These results are seen in the boxplots for Workload (Figure 21), Situation Awareness (Figure 22), and Trust (Figure 23).

Further analysis was conducted using contrast B. These results are in Table 31. When the TOR is introduced at predictable failure events, the participant's perceived Workload decreases by an average of 10.5, the Situation Awareness increases by an average of 3.7, and the Trust also increases by 0.68 points. These results show that driver's likely were more aware of the failure events when the TOR was present at predictable failures, thus improving their performance.

Table 31: Effect of introducing TOR for predictable failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Workload	-10.48	t(35)=-2.99	0.005	-17.59	-3.38
Situation Awareness	3.7	t(35)=3.43	0.0016	1.51	5.89
Trust	0.68	t(35)=3.57	0.001	0.29	1.06

Mean	**35.96**	**32.02**	**39.1**	**28**	**41.48**	**31**	**38.48**	**35**
S.D.	17.61	19.18	19.83	17.32	14.53	16.28	15.49	18.73

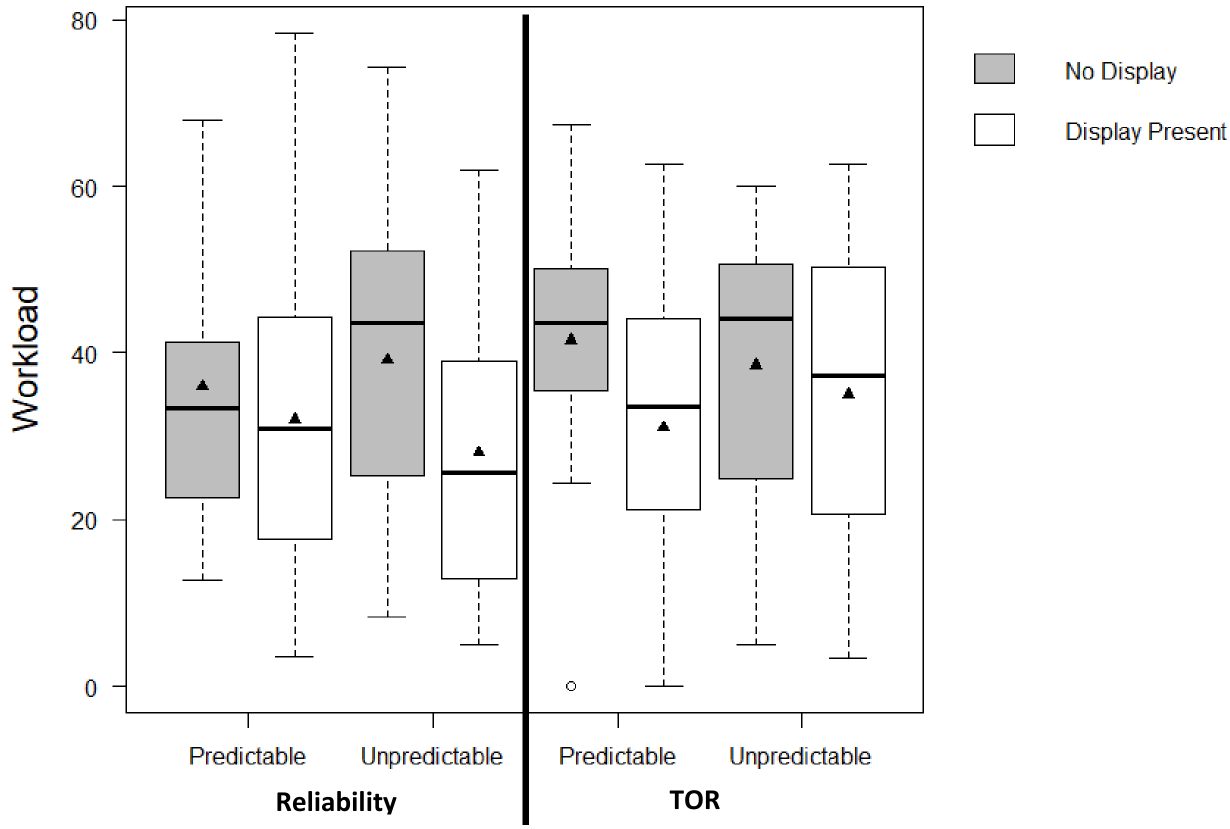

Figure 21: Boxplot of the raw data for Workload

Mean	**22.65**	**24.82**	**20.35**	**22.41**	**22.55**	**26.25**	**24.95**	**25.95**
S.D.	9.14	8.35	8.51	10.07	6.13	6.09	3.36	3.15

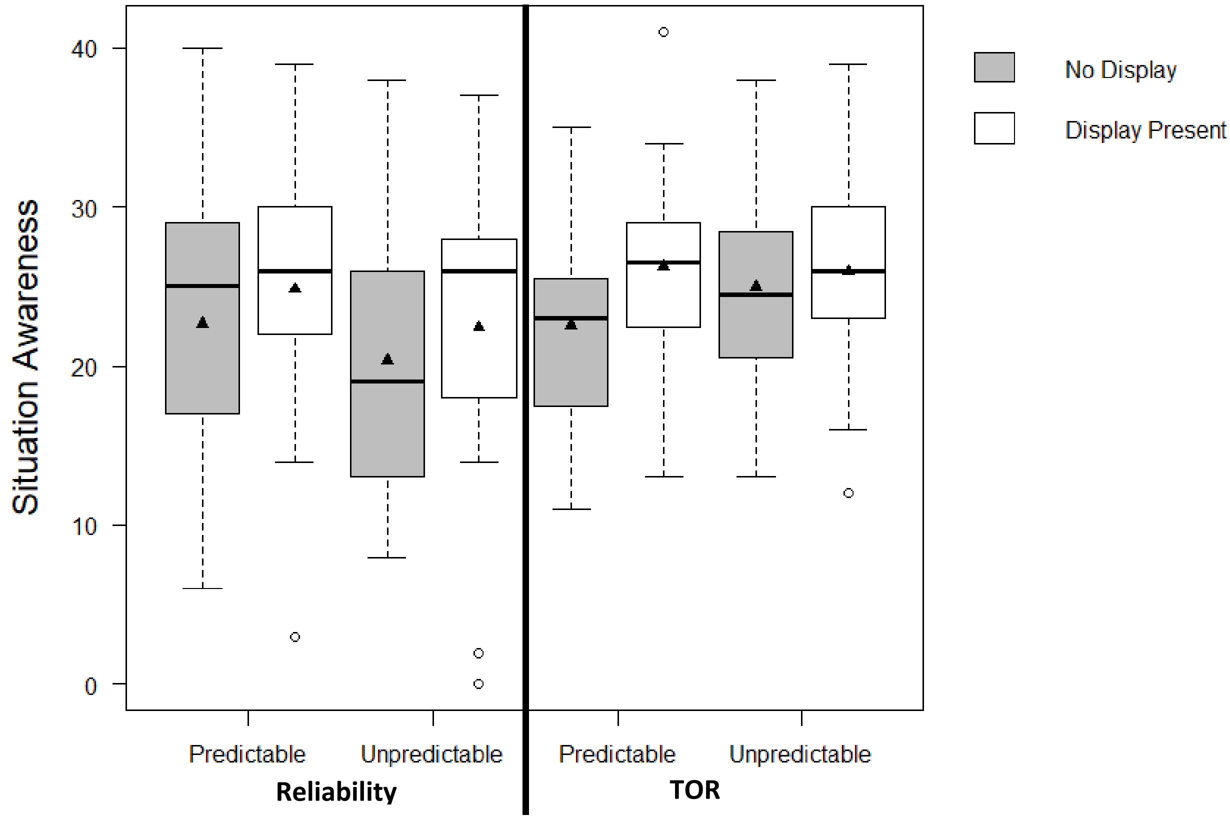

Figure 22: Boxplot of the raw data for Situation Awareness

Mean	**4.85**	**5.53**	**4.63**	**5.5**	**4.57**	**5.25**	**4.43**	**4.89**
S.D.	1.33	1.17	1.58	1.33	0.93	1.15	0.97	1.24

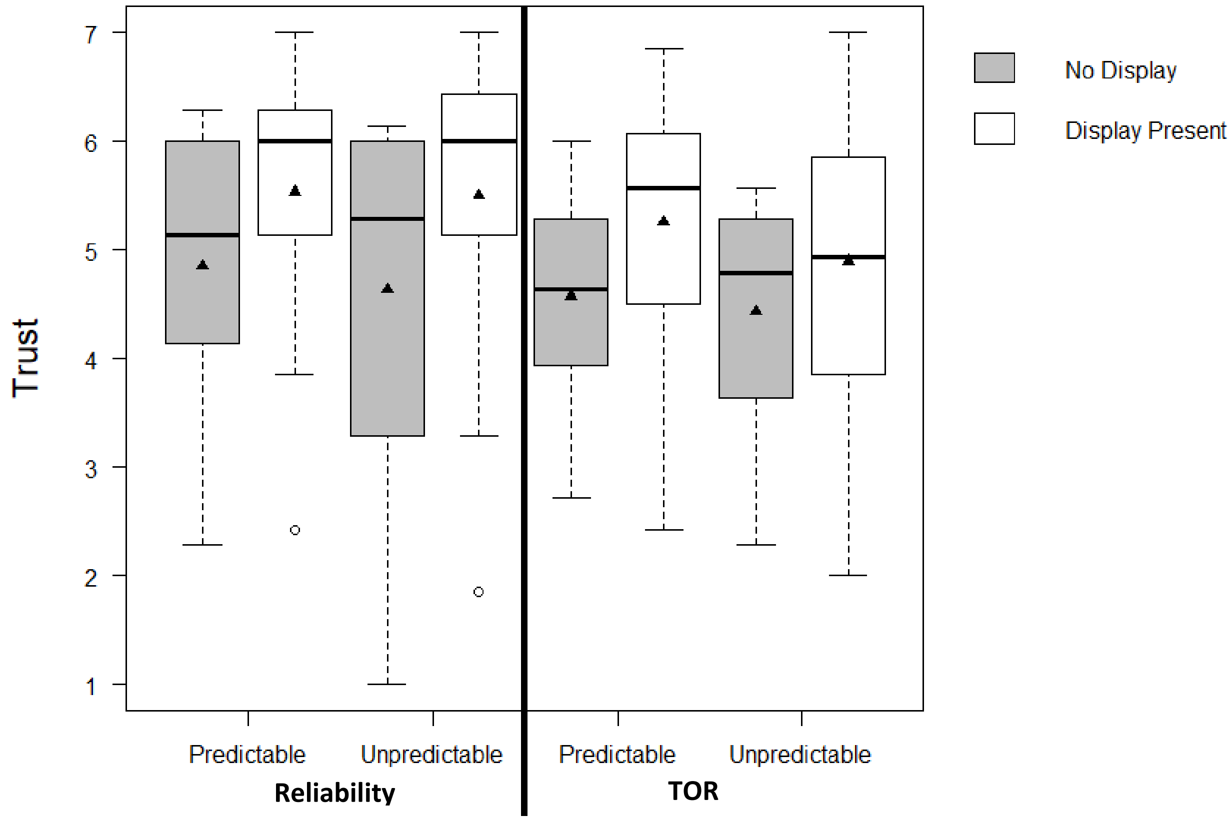

Figure 23: Boxplot of the raw data for Trust

Effect of Introducing TOR at unpredictable failures

When the TOR was introduced at unpredictable failures, participants had more trust in the automation. This relationship is visible in the boxplot for Trust (Figure 23).

Additional analysis was performed using contrast C, and the results are in Table 32. These results show that participants seemed to Trust the system more when the TOR was introduced at unpredictable failures, as there was an average increase of 0.46 in Trust.

Table 32: Effect of introducing TOR for unpredictable failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Trust	0.46	t(35)=2.44	0.02	0.79	0.85

Difference in the effect of introducing TOR at predictable versus unpredictable failures

A visual inspection of the data does not show a difference in the effect of introducing TOR at predictable versus unpredictable failures. Further analysis with contrast D did not show any significant results.

6.3.3 Effect of introducing a reliability display (reliability display versus no display)

The effect of introducing the reliability display is broken down into three areas: 1) the effect of introducing a reliability display at predictable failure events, 2) the effect of introducing a reliability display at unpredictable failure events, and 3) the difference in the effect of the introduction of a reliability display at predictable failure events versus unpredictable failure events.

When the reliability display was introduced, participants experienced greater satisfaction and trust at predictable failure events. When the reliability display was introduced at unpredictable failure events, participant's also perceived their workload to be lower, and they experienced greater usefulness, satisfaction and trust with the automation.

Effect of introducing a reliability display at predictable failures

When the reliability display was introduced at predictable failure events, participants appear to Trust the automation more (Figure 23), and they appear to have more Satisfaction in the system (Figure 24).

Further analysis was performed using contrast E. The results are presented in Table 33. The results show that on average, participant's Satisfaction increases by 0.37 when the reliability display is introduced at predictable failure events. The driver's Trust also increases by 0.68 when the reliability display is introduced at predictable failure events.

Table 33: Effect of introducing a reliability display for predictable failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Satisfaction	0.37	t(35)=2.94	0.006	0.11	0.62
Trust	0.68	t(35)=3.3	0.002	0.26	1.1

Mean	**0.82**	**1.19**	**0.81**	**1.22**	**1.01**	**1.24**	**0.98**	**1.19**
S.D.	1.03	1.02	1.12	0.88	0.67	0.6	0.7	0.65

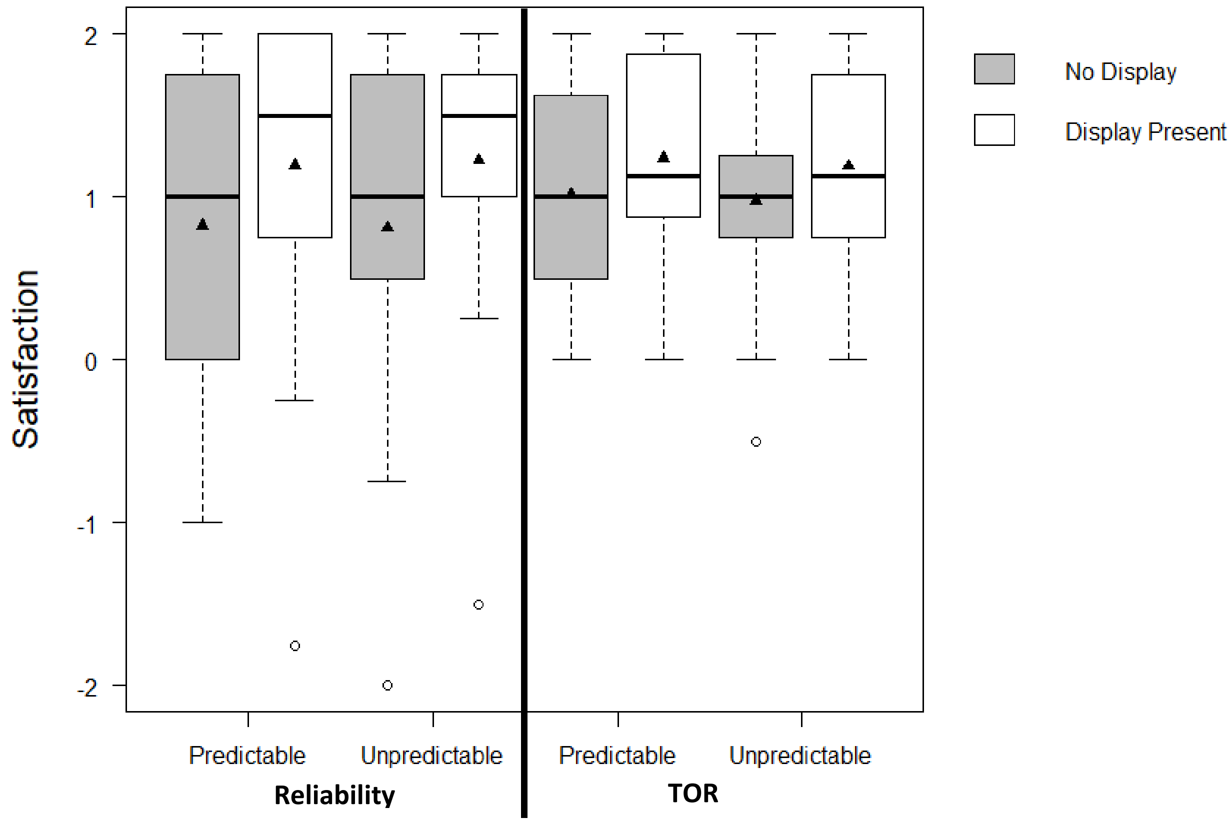

Figure 24: Boxplot of the raw data for Satisfaction

<u>Effect of introducing a reliability display at unpredictable failures</u>

When the reliability display was introduced at unpredictable failure events, participant's experienced a decrease in their Workload (Figure 21), and their acceptance of the system appears to increase as their Satisfaction and Usefulness increases (Figure 24 and Figure 25). Additionally, participants appear to trust the system more (Figure 23).

Further analysis was performed using contrast F. The results are in Table 34**.** The results show that participant's Workload decreased by an average of 11.1 when the reliability display was introduced at unpredictable failures. Participant's also experienced a significant increase in how they accepted the automation. When the reliability display was introduced at unpredictable failure events, driver's Usefulness of the automation increased by 0.36 on average, and their Satisfaction with the automation increased by 0.41 on average. Participant's Trust of the automation also increased by 0.87 on average when the reliability display was introduced at unpredictable failure events.

Table 34: Effect of introducing a reliability display for unpredictable failures

	Estimate	t-Value	p-Value	95% CI: Lower	95% CI: Upper
Workload	-11.1	t(35)=-2.92	0.006	-18.81	-3.39
Usefulness	0.36	t(35)=2.91	0.0062	0.11	0.62
Satisfaction	0.41	t(35)=3.30	0.002	0.16	0.67
Trust	0.87	t(35)=4.2	0.0002	0.45	1.28

Mean	**0.66**	**0.84**	**0.61**	**0.98**	**0.91**	**1.07**	**0.88**	**1.05**
S.D.	0.95	1.02	0.97	0.93	0.66	0.68	0.68	0.62

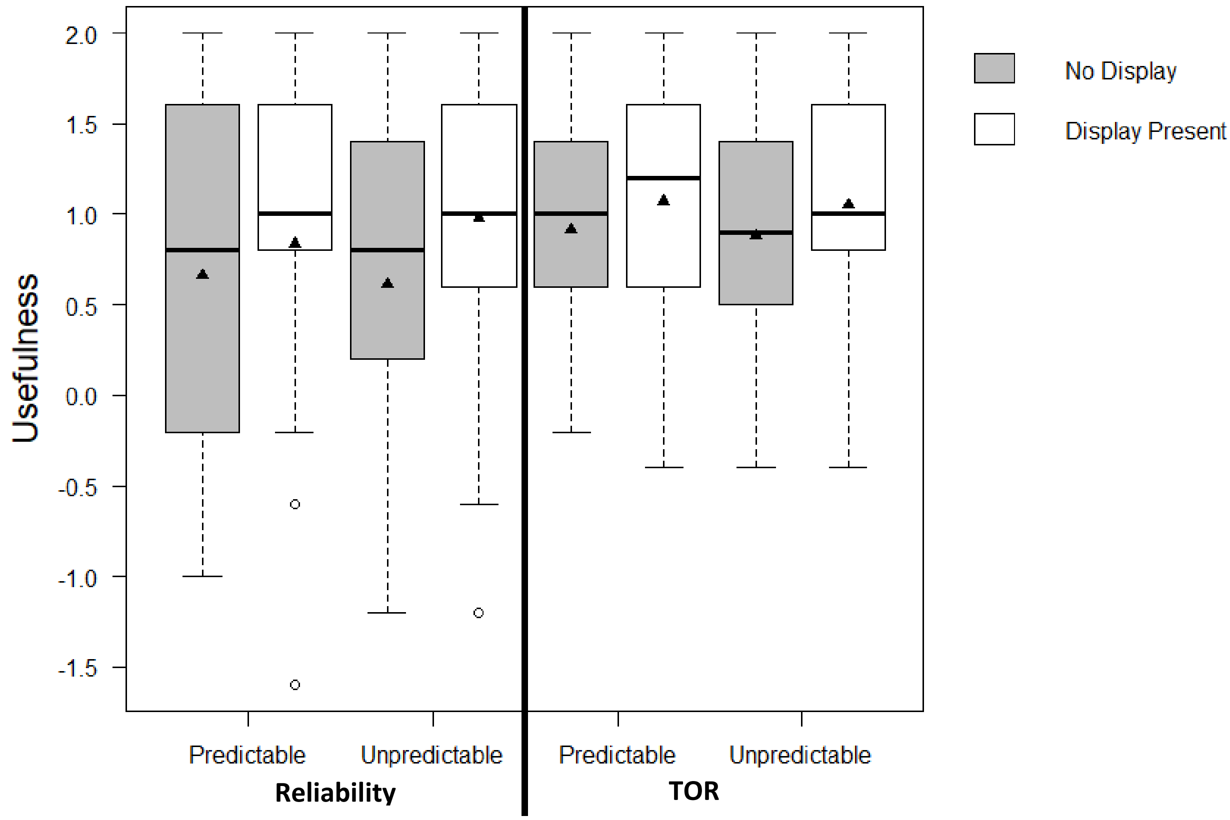

Figure 25: Boxplot of the raw data for Usefulness

<u>Difference in the effect of introducing a reliability display at predictable versus unpredictable failures</u>

There was no relationship that was visible upon an inspection of the boxplots. Further analysis was performed using contrast G, however, there were no significant results.

6.3.4 Difference between introducing TOR and reliability displays

There was no significant difference between the TOR and the reliability display.

Chapter 7

7 Discussion

Given the two research objectives of this study, discussion of the results is broken down into the following two segments of research: 1) the effect of failure type on takeover, and 2) the comparison of the TOR to the reliability display.

7.1 Effect of failure type on takeover

The results show that when no display was present, there was a decrease in the Hands-On-Wheel Time and a larger odds ratio for Hands-On-Wheel Prior to Failure for predictable failures as compared to unpredictable failures. Thus, when no display was present, drivers prepared sooner for a takeover event when there was a predictable failure than when there was an unpredictable failure. Additionally, at predictable failures, drivers were significantly more likely to prepare prior to the start of the failure than at unpredictable failures. These results partially confirm hypothesis H1. Hypothesis H1 cannot be fully confirmed as there was no significant difference in the Take-Over Time, which shows that participants did not takeover sooner at predictable failures than at unpredictable failures. While participants prepared for the failure event sooner for predictable failures than unpredictable failures, it appears that participants tended to only takeover once the failure events commenced, regardless of the failure type. This may be explained by the non-critical nature of the predictable failure event—even if a participant did not takeover, there was no risk of crashing, and therefore, a participant could wait and see how the vehicle behaved, and then takeover. As participants had already experienced the failure events in the training drive, they likely knew about the non-critical nature of each of the failure events.

The results did not confirm Hypothesis H2 as the majority of the takeover quality variables (Maximum Acceleration After Takeover, Steering Wheel Angle Range, and Max Steering Wheel Angle) did not show any significance. However, there was a significant increase in the standard deviation of steering wheel angle at predictable failure events as compared to unpredictable failure events. According to a definition of the standard deviation of steering used by Shen and Neyens (2014), the increase in this variable indicates a poorer driving performance when drivers encounter predictable failure events than unpredictable failure events, which would disprove hypothesis H2. Yet, according to the definition of the standard deviation of steering provided by Eriksson and Stanton (2017a), the increase in the standard deviation of steering could be indicative of the greater effort exerted by drivers to maintain the position of the vehicle in the lane at the predictable failures, which would neither confirm nor disprove hypothesis H2. As more effort is required on the part of the driver to navigate through an intersection during the predictable failures, versus driving in a straight line at unpredictable failures, the Eriksson and Stanton (2017a) definition of the standard deviation of steering likely explains why there is a significant increase in this variable Therefore, more research must be performed to evaluate whether there is a significant difference in drivers' takeover quality for predictable versus unpredictable failures, by looking at different types of predictable failures (see Table 1 for examples), and having a comparable unpredictable failure.

Confirming hypothesis H3, there was a 36% decrease in the driver's rate of interactions with the secondary task prior to the predictable failure events as compared to the unpredictable failure events. According to the work of Schömig, Metz, and Krüger (2011), which showed that the rate of a driver's interaction with the secondary task is inversely related to the driver's situation awareness, this decrease in the rate of interactions in the secondary task at predictable failures suggests that participants were more aware of the impending predictable failure events than the unpredictable failure events, and therefore decreased their rate of interaction in order to prepare for the takeover. As the secondary task was visual-manual, the decrease in the rate of interactions likely means that the drivers were monitoring the road more during this time, consistent with the results of Dogan et al. (2017), which showed that when participants were provided with anticipatory information, their rate of monitoring increased.

There were no significant effects on self-reported measures of workload, situation awareness, trust, acceptance, or perceived risk, and therefore hypotheses H4 and H5 are not confirmed. As the questionnaire for the self-reported measures was only given to the participants at the end of each drive (i.e., after they experienced two failure events), the data therefore consists of the driver's perception of both failures, rather than just the first failure, which was the only failure that was analyzed above. Given that the second predictable failure event proceeded in a manner that was different from the first predictable failure event and was difficult for the participants to anticipate, it is likely that the questionnaire data was impacted. Therefore, the self-reported measures likely do not provide an accurate assessment of the difference between predictable and unpredictable failures. More research must then be conducted to determine whether hypotheses H4 and H5 hold true using the self-reported measures. However, as stated above, the decrease in the driver's rate of interaction with the secondary task at predictable failure events as compared to unpredictable failure events suggests that drivers had increased situation awareness at predictable failures (Schömig et al., 2011), providing support for hypothesis H5.

While additional research is required to further understand the effect of failure type on takeover, overall, it is clear that when drivers are able to perceive an impending failure event, they prepare for the impending failure event sooner and decrease their rate of interactions with the secondary task, which suggests that drivers have an improved situation awareness. Although there was no effect of failure type on takeover quality, if drivers are trained to takeover as soon as they put their hands on the wheel, or as soon as drivers perceive a possible failure event in the distance, drivers likely will have an improved takeover quality when they takeover.

As all participants in this experiment were trained to recognize the predictable failures, for future research, it would be interesting to see and qualify the impact of training on participant's ability to recognize the predictable limits of the automation on participant's takeover quality. Another area of future research would include testing the impact of different types of predictable failures on a participant's takeover quality.

7.2 Comparison between TOR and the Reliability Display

To ease the comparison of these displays, each of the different measurements that were used are discussed separately. In each section, each of the displays are first compared to the no display condition, and then compared to each other. Additionally, it is beneficial to look at how each of the displays fared on its own in comparison to previous research on the use of each of these displays, to verify how this research compares to the compendium of research that is currently out there.

Furthermore, the results that are presented below are for both predictable and unpredictable failures, unless otherwise specified.

7.2.1 Response Time

Covariate analysis showed that when drivers prepare for and takeover control of the automation prior to failure events, regardless of failure type, there is a significant improvement in the driver's takeover quality. While this covariate analysis has not previously been performed, given that a significant portion of research in automated driving has mostly been to decrease the driver's reaction time by providing them with advance notice of potential failures, it is clear previous research indicates a benefit of early takeover. This result therefore adds to the previous research by providing a clear demonstration of the impact of the stage of takeover on takeover quality.

Introducing the TOR (TOR versus No Display)

Results show that when the TOR was compared to no display, participants responded faster to an impending failure event, by putting their hands on the wheel sooner, and by taking control of the automation sooner than when there was no display. Additional analysis showed that participants were more likely to put their hands on the wheel prior to a failure event when there was a TOR than when there was no display. While the failures in this experiment were all in the lateral direction, these results are nonetheless consistent with all of the previous work on the use of TORs for failures in the longitudinal direction, which show faster response times when the TOR is introduced than when there is no TOR (Damböck et al., 2012; J. Lee et al., 2006; Melcher et al., 2015; Naujoks & Neukum, 2014; Ruscio et al., 2015). These results are also consistent with the work of Naujoks et al. (2014), which uses TORs for lateral direction failure events.

Introducing the Reliability Display (Reliability Display versus No Display)

When the reliability display was compared to no display, participants readied themselves sooner for the failure event and they took over control of the automation sooner, as indicated by the results for the participant's Hands-On-Wheel Time and Take-Over Time. These results are consistent with the work of Helldin et al. (2013), who used a similar display, as well as other research that provided participants with uncertainty displays, system confidence information, and system limits (Beller et al., 2013; Seppelt & Lee, 2007; Stockert et al., 2015), which showed a faster response time and takeover time.

TOR versus Reliability Display

Results showed that participants took over control of the automation on average 1.8 seconds sooner at predictable failures and 2.2 seconds sooner at unpredictable failures when the reliability display was introduced than when the TOR was introduced, therefore confirming hypothesis H6. Given the odds ratio for Take-Over Prior to Failure, participants also were significantly more likely to takeover prior to the failure event when there was a reliability display present than when there was a TOR display present. These results may be because participants had more time to decide when to takeover, as the vehicle's reliability started decreasing 26 seconds prior to the failure event, compared to the TOR display which only appeared 6 seconds before the failure event. Additionally, with the knowledge that there would be an impending issue with the automation, participants may have felt uncomfortable relying on the automation when it started decreasing, and therefore wanted to drive manually as soon as the reliability went below the threshold.

While participants took over control of the automation sooner when the reliability display was present, there was no significant difference between the displays regarding how soon participants put their hands on the wheel. Regardless of the display, participants put their hands on the wheel nearly as soon as the reliability display went below its threshold or when the TOR appeared. It is likely that participants put their hands on the wheel prior to the failure event for both displays because each display had an aural component which conveyed a sense of urgency (Naujoks et al., 2014).

Therefore, while participants put their hands on the wheel at roughly the same time for each display, they turned off the automation sooner when the reliability display was present, likely due to the inherent difference between what the displays are communicating to the drivers. The reliability display provides drivers with continuous feedback about the status of the automation and informs them when the limits of the automation's abilities will soon be reached, while the TOR only informs drivers when they need to take control of the vehicle. This additional transparency for the reliability display provides the driver with more time than the TOR to be aware that a transfer of control may soon be necessary, allowing drivers more time to gain situation awareness and takeover early.

<u>Introduction of a display at different failure types</u>

While display type did not influence how soon participants placed their hands on the wheel, it is interesting to note that for both displays, participants put their hands on the wheel significantly later when at predictable failures than at unpredictable failures. This is the opposite of the result for when no display present at each failure type (section 7.1), and may be attributed to the information that each display provides participants about when to takeover. When drivers saw the reliability of the automation decreasing or the TOR appear during the predictable failure drives, drivers may have looked more frequently towards the road and seen the upcoming intersection, and know when the failure was going to occur, and thus wait to takeover. Given the discussion of the automation's limitations prior to start of the experiment, and that participants experienced an automation failure at an intersection during the training drive, participants likely were aware of where the car would fail, and therefore could complete the secondary task they were on, and could take longer to put their hands on the wheel, and have a more comfortable transition period. On the other hand, when the reliability display decreased or the TOR appeared in the unpredictable failure drives, while drivers may have still glanced at the road more frequently, there were no external cues indicating why the automation would no longer be reliable, and therefore, it is likely that participants put their hands on the wheel sooner because the location of the failure event was unclear. Even though participants were briefed prior to the experiment that when the reliability display's threshold was reached, or when the TOR appears, that they would have 6 seconds to takeover, participants likely were not counting down the time until the failure, and rather were relying on external cues to determine when the failure would occur. Without external cues, it is then likely that the aural cue from each display 6 seconds prior to the failure event made the experience seem more urgent, therefore prompting the driver to put their hands on the wheel sooner (Naujoks et al., 2014).

7.2.2 Take-Over Quality

<u>Introducing the TOR (TOR versus No Display)</u>

For both failure types, the TOR improved the driver's takeover quality—drivers experienced less accelerations after the failure event, moved the steering wheel less, and spent less time out of the lane. These results are consistent with the available research on the use of TORs (Damböck et al., 2012; J. Lee et al., 2006; Melcher et al., 2015; Naujoks et al., 2014; Naujoks & Neukum, 2014; Ruscio et al., 2015).

Introducing the Reliability Display (Reliability Display versus No Display)

For both failure types, with the reliability display, participants showed an improved takeover quality, with less overall acceleration, less steering wheel movement and less time out of the lane. These results are consistent with previous work using displays to provide additional information to drivers at safety critical events during manual driving, which showed that these displays improve the participant's driving quality with earlier and reduced decelerations in response to on-road obstacles (Laquai, Chowanetz, & Rigoll, 2011; Popiv, Christoph, Bengler, & Duschl, 2010). In the domain of automated driving, the results presented here are consistent with the results of Beller et al. (2013), who showed that when drivers were presented with an uncertainty display, they maintained a significantly larger minimum Time to Collision gap with the lead vehicle, and thus shows improved driving ability.

TOR versus Reliability Display

When the reliability display is compared to the TOR, the results show that drivers have a better takeover quality at predictable failure events with the reliability display than the TOR. This is indicated by the decrease in the standard deviation of steering, and the decrease in the range of the steering wheel angle when the reliability display was introduced as compared to when the TOR was introduced. As the reliability display started decreasing 26 seconds prior to the failure event, the driver may have looked up at the road more frequently to monitor the driving environment, and gained situation awareness about the impending failure event when they saw the intersection. This improved situation awareness could have helped the drivers understand the situation and respond accordingly to the failure event.

However, the benefit of the reliability display over the TOR on a driver's takeover quality is not apparent at unpredictable failure events. One reason for this may be that even with the decreasing reliability to encourage the drivers to monitor the driving environment, at unpredictable failures, there were no external cues to help drivers anticipate what type of failure may occur, which would have helped them prepare for the failure and have a better takeover quality. Without external cues to help drivers see when and where a failure would occur, participants relied more upon the reliability display going below the threshold to indicate when the failure event would happen, thus making their usage of the reliability display similar to that of the TOR. This would mean that at unpredictable failures, simply having a display present provided drivers with enough time to prepare for a failure, and have a better takeover quality than with no display present.

These results therefore partially confirm hypothesis H7. The reliability display resulted in a better takeover quality for predictable failure events, however, at unpredictable failure events, there is no clear benefit between the two displays.

7.2.3 System Acceptance

Introducing TOR (TOR versus No Display)

There was no significant difference in the participant's system acceptance when the TOR was introduced.

Introducing Reliability Display (Reliability Display versus No Display)

When the reliability display was introduced at both predictable and unpredictable failures, there was a significant increase in the driver's satisfaction with the automation. At unpredictable failure events, there also was a significant increase in the automated system's perceived usefulness. These results are consistent with previous research which showed a higher system acceptance for their monitoring request and informational displays (Gold, Damböck, Bengler, et al., 2013; Kraft et al., 2018) (see Table 2 for details on each display). Participants likely perceived the system to be more useful and satisfactory because it provided them with information they otherwise could not have gleaned themselves, and thus helped them prepare for failures.

TOR versus Reliability Display

There was no significant difference in system acceptance between the TOR and the reliability display. Therefore hypothesis H8 is not confirmed. However, as the experiment was a between-subject experiment, participants never experienced both displays, and therefore, were this a within-subject experiment and participants could experience each display, participants may have rated their acceptance of the automation differently.

7.2.4 Secondary Task Engagement

Introducing the TOR (TOR versus No Display)

When the TOR was compared to no display at unpredictable failures, there was a significant decrease in the participant's secondary task engagement 30s prior to the failure. This shows the benefit of the TOR, as without it, participants would be unaware of an impending failure event, and would otherwise not decrease their secondary task engagement to prepare for the failure. According to the work of Schömig and Metz (2013), this decrease in secondary task engagement may be indicative of an increase in the participant's situation awareness.

At predictable failures, there is no significant difference in the participant's rate of interaction with the secondary task when the TOR is introduced. This may be because participants regularly looked up to the road and saw the upcoming intersection with indicated the failure, and thus interacted with the secondary task significantly less regardless of whether the display was present.

These results show that TORs are beneficial in decreasing the driver's rate of interaction with a secondary task when there is no anticipatory information in the environment.

However, when the rate of interaction with the secondary task was compared at predictable and unpredictable failures for the TOR, the contrast shows that there was a significant increase in the rate of interaction 30s prior to predictable failures than unpredictable failures. This result is not consistent with the results looking at the introduction of the TOR at either predictable or unpredictable failures, or with the results when no display was present. This result may originate in the large range for the number of interactions for participants 30s prior to a predictable failure with no display present, and the significantly smaller range for predictable failures when the TOR is present, as shown in the boxplot in Figure 20. As the boxplot shows that both of these groups of data have nearly the same mean, it is possible that their range may have skewed the result from the contrast analysis.

If this result is correct, however, it may be explained by how, at predictable failures, participants could look up from the secondary task, and see the intersection, and know exactly when the failure event would occur because they had previously experienced a predictable failure at an intersection in the training drive. Therefore, with this knowledge, participants could complete the task they were performing and still have enough time to spare for a safe takeover. At unpredictable failure events, participants decreased their engagement in the secondary task, likely because they could not immediately understand why the automation was failing, and thus were attempting to gain situation awareness.

Given the lack of clarity in the results of the comparison between the use of the TOR display at predictable and unpredictable failures, additional research should be conducted in the future to further understand how the TOR display interacts with the failure type, and how they impact a participant's secondary task engagement.

Introducing the Reliability Display (Reliability Display versus No Display)

Participants decreased their use of the secondary task at unpredictable failure events when the reliability display was introduced. These results are consistent with the results of (Beller et al., 2013; Stockert et al., 2015), which showed that drivers decreased their use of the secondary task when the displays showed that the vehicle's automation was uncertain about an upcoming event, which by the classification in this thesis, would be an unpredictable failure.

There was no significant difference in the driver's rate of interaction with the secondary task at predictable failures when the reliability display was introduced. This is because participants already interacted with the secondary task significantly less at predictable failure events regardless of whether the reliability display was present (the results discussed in 7.1 show that with no display, participants interacted with the secondary task less at predictable failures than unpredictable failures), as they could see the location of the impending failure each time they looked up from the task. Therefore, drivers likely decreased their use of the secondary task to improve their situation awareness.

TOR versus Reliability Display

There was no significant difference in the rate of secondary task engagement when the reliability display was introduced versus when the TOR was introduced. This likely is due the overall benefit that simply introducing a display provides.

Introduction of a display at different failure types

When either display was introduced, drivers significantly decreased their rate of interaction with the secondary task at unpredictable failure events. It is likely, therefore, that when the displays notified participants that there would be an impending failure, they immediately decreased their use of the secondary task at unpredictable failures and then may have increased their glances towards the road as they were not sure about when the failure would occur. This result is consistent with the work of Beggiato et al. (2015), which showed that drivers had less engagement in the secondary task when they were driving in more complex scenarios – when the TOR was issued and the reliability threshold was reached, drivers had to be ready for a takeover event and understand what was going to occur next, which inherently is complex. Given the work of Schömig and Metz (2013), participants may have had greater situation awareness at unpredictable failures as they decreased their use of the secondary task.

However, there was no significant change in the participant's rate of interaction with the secondary task at predictable failures. This may be due to participants decreasing their secondary task engagement once they can see the intersection, with or without a display, so they can increase their situation awareness.

7.2.5 Trust

Introducing the TOR (TOR versus No Display)

According to the results of this experiment, the use of the TOR appears to be effective in increasing participants' trust of the automated system. This makes sense as participants could rely on the TOR to inform them of an impending failure, and therefore have a clear idea of the automation's capability. However, it is likely that it was not the use of the TOR alone that increased participants' trust in the automated system, but its use in conjunction with their familiarization with the TOR prior to using it in the system, as during the familiarization session, participants were told that the TOR was a reliable alert (Koustanaï et al., 2012).

Introducing the Reliability Display (Reliability Display versus No Display)

The introduction of the reliability display also showed a significant increase in system trust, which is consistent with previous research that was conducted using uncertainty and reliability displays (Beller et al., 2013; Stockert et al., 2015). The introduction of the reliability display improved the driver's trust in the automation as it clearly provided the drivers with an understanding of the automation's capabilities at any given moment, and informed drivers of whether they would be required to intervene in the driving task.

TOR versus Reliability Display

The results did not show any significant difference in trust between the introduction of the reliability display and the introduction of the TOR. As the introduction of both displays increased the drivers trust in the automation, the between-subject nature of this experiment likely did not have the levels of precision necessary to show an accurate comparison in participants' self-reported measures.

7.2.6 Situation Awareness

As the questionnaires to collect the driver's self-reported measures were only submitted to the drivers after each experimental drive, the results for the self-reported measure of a driver's situation awareness are likely impacted by the second predictable failure event, which drivers could not anticipate and thus was not actually predictable.

Introducing the TOR (TOR versus No Display)

When the TOR was introduced at predictable failure events, there was a significant increase in the participant's perceived situation awareness. Given the lack of predictability of the second predictable failure event, this result makes sense, as the TOR informed drivers of the failure event, thus ceasing the driver's need to attempt to determine if a takeover was necessary. However, there was no significant change in the participant's situation awareness when the TOR was introduced at unpredictable failure events, likely because there was no clear indicator of why the automation was failing.

Introducing the Reliability Display (Reliability Display versus No Display)

There was no significant difference in the driver's situation awareness when the reliability display was introduced for either predictable or unpredictable failures. While the boxplot in Figure 22 does not show any significant results, it does show an increase in the average situation awareness from no display to the reliability display for both failure types. A significant result was expected here due to the decrease in the driver's rate of interaction with the secondary task with the reliability display present. This lack of significant difference may be due to the self-reported nature of this data, and how some participants may find the questions obscure.

TOR versus Reliability Display

There was no significant difference in situation awareness between the reliability display and the TOR. It is likely that these results were impacted by the between-subject nature of this experiment, as participants who experienced both display types would probably respond to the SART questionnaire comparing the two displays.

7.2.7 Workload

Introducing the TOR (TOR versus No Display)

The introduction of the TOR at predictable failure events significantly decreased the driver's workload. At first glance, this result does make sense as it created an accurate warning system which allowed drivers to not monitor the road if they so desired, thereby decreasing the participant's subjective workload (Ma & Kaber, 2005; N.A Stanton et al., 1997; Neville A. Stanton & Young, 2005). However, the workload does not show a significant decrease when the TOR is introduced at unpredictable failure events, which is inconsistent with this theory. Thus, it is likely that the workload data was also impacted by the second predictable failure event, and the TOR decreased participants' workload as it would have confirmed the failure at the second intersection meaning that participants no longer had to guess whether an issue would occur.

Introducing the Reliability Display (Reliability Display versus No Display)

Contrary to what was found with the TOR display, there was a significant decrease in participants' workload when the reliability display was introduced at unpredictable failures. A possible reason for this result may be because participants were told that they could rely upon the display, and therefore, only felt that they needed to start monitoring the environment once the reliability display started decreasing from Levels 4 or 5. This extra time monitoring the environment, as compared to the TOR, may have then enabled these drivers to realize that there were no external cues indicating a failure, and thus decreased their workload as they didn't have to keep guessing as to why the automation was failing.

It is interesting to note, however, that when the reliability display is introduced at predictable failures, there is no significant change in the driver's workload. There is no clear reason for this, but it may be due to the drivers in the reliability display group having a clear idea that the predictable failures would occur at the intersections even when the display was present. This clear mental model of the automation's capabilities would not be affected by the introduction of a reliability display.

TOR versus Reliability Display

The results did not show any significant difference in the participant's workload when the reliability display was introduced as compared to the introduction of the TOR. This lack of significance may be due to the between-subject nature of this experiment. Additional research is required to clarify whether there is a difference in workload between a TOR and reliability display.

7.3 Limitations and Future Research

There were several limitations in this experiment. One limitation, as discussed above, is the impact of the second predictable failure event on the self-reported measures. As the questionnaires were only given to the participants after they experienced both predictable failures, the impact of the recency bias due to the design of the second predictable failure event likely impacted the participants' responses to the questionnaires. For future research, it would be recommended to design all failures that participants experience to progress in the same manner. One way to accomplish this would be to use triggers to create consistent failures across every condition.

Another limitation of the experiment was that drivers could only takeover with the steering wheel by moving the steering wheel past 5° from the center. This takeover method, while necessary to prevent the participants from accidentally turning off the lane keeping was less intuitive than simply turning off the lane keeping once the drivers placed their hands on wheel, or moving the steering wheel by 1 degree. Even though most participants put their hands on the wheel prior to a failure event when a display was present, less than half of the participants turned off the automation before the failure event. It is possible that the participants did not intuitively realize that putting their hands on the wheel did not turn off the automation (even though this was practiced prior to the experimental drives). Results may have been different if the level of steering wheel movement to turn off the automation could have been less. It is therefore recommended that for future research, the steering wheel becomes more sensitive to driver input to turn it off.

Another possible limitation of this experiment was that due to issues with the steering wheel's sensitivity, drivers could only turn the lane keeping on when they were on a straight portion of the road. Therefore, participants turned on the lane keeping at different points during the experiment, and likely had a higher workload because they were required to remember to turn on the lane keeping in addition to performing the secondary task. For future experimentation, it would be beneficial to create a steering wheel that moved with the wheels of the vehicle so that this issue could be avoided, and participants could turn on both the ACC and the lane keeping when they are prompted by the computer.

As each experimental drive was 6 minutes long, and the overall experiment lasted around 2.5 hours, drivers were likely more motivated to search for the salient cues that indicated the limits of the automation that were taught during the training session (in this experiment, the salient cue that indicated an automation limit was the predictable failures in the form of intersections), than they would have been if this experiment took place over a longer period of time, or several weeks. It would be interesting if future research looked at the impact of training on the driver's ability to takeover over a period of several weeks, similar to the set-up used in the work of Beggiato and Krems (2013).

While the use of lateral failures has been validated in earlier work performed by Shen and Neyens (2014, 2017), the use of lateral failures in automated driving research is not widespread. This therefore is a limitation of this research, and future research should examine the use of longitudinal failures to create each of these failure events.

Another limit of this thesis is that it has not yet looked at the results from the eye tracking data. Future research should explore how each of the displays impacts a driver's monitoring and glance data.

As the between-subject nature of this experiment may have impacted some of the results, such as the self-reported measures, for future research, it would be beneficial to create a within-subject experiment comparing how drivers respond to both the reliability display and the TOR.

As the reliability display in this experiment only decreased prior to an automation failure, and always told the participants when the automation would fail, future research should examine reliability displays that act more like the uncertainty display described in Beller et al. (2013), where it appeared at a possible takeover scenario, but no critical event occurred. Therefore, the design of this future reliability displays should increase and decrease, creating a situation similar to a false alarm, but rather indicates to the participant that the automation is less reliable, or below a certain threshold, the automation's capabilities are not guaranteed. The benefit of this research would be that it is more indicative of actual reliability systems.

Chapter 8

8 Conclusions

8.1 Contributions

Vehicles are only going to become more automated and more common in the coming years. Until the vehicle's automation is at SAE Level 5, humans are still required to be in the loop and monitor the driving environment in case of a potential failure situation. The study presented in this thesis addressed the two research gaps discussed in section 2.4.

8.1.1 Objective 1—Failure Type Comparison

The results from this experiment quantify the differences in driver performance when taking over control of the vehicle at predictable and unpredictable failures when no display is present. As expected, drivers are more aware of an impending failure when they encounter predictable failures than unpredictable failures, as drivers put their hands on the wheel sooner, and decrease their rate of interaction with the secondary task prior to the predictable failures. These results suggest that comparing driver takeover between these two types of failure events may not be acceptable, or provide accurate results. These findings should be further explored using different types of predictable failure events (see Table 1 for examples), as well as failures in the longitudinal direction. A better understanding of how drivers of automated vehicles use external cues to anticipate when a vehicle failure could occur (i.e. predictable failures) would help vehicle manufacturers write owner manuals or develop warning systems to help drivers recognize these predictable failure events. This better understanding may also help vehicle manufactures realize the necessity of a training session with drivers prior to ownership to ensure that all drivers are able to recognize these predictable failures. An improved understanding of the differences between predictable and unpredictable failures may also help designers create warning systems that help drivers prepare for unpredictable failures and understand that not all failures have external cues.

8.1.2 Objective 2—Display Comparison

Additionally, the results of this experiment suggest that the reliability display may be more beneficial to drivers than the TOR display, as drivers took over control of the vehicle sooner when the reliability display was present than when the TOR was present. Drivers also had an improved takeover quality at predictable failure events when the reliability display was present compared to the TOR. These findings should be further explored with different forms of reliability displays. If the reliability display continues to show benefits over the TOR, it may be advantageous for car manufacturers to start developing these displays and adding them to their vehicles.

8.1.3 Additional Findings

Furthermore, this research also suggests that simply having a display present had positive effects on drivers, as both displays showed a decrease in the drivers' reaction time and improvement in their takeover quality. Both displays also showed that drivers decreased their interaction with the secondary task prior to unpredictable failures, and drivers had an increased trust in the automation. Individually, the benefits of each of these displays confirms previous research. These findings indicate that car manufacturers should continue to implement auditory-visual displays in their automated vehicles to improve driver performance.

One unexpected result of having a display present, however, was that when drivers did not have a clear understanding of why the automation was failing (i.e. unpredictable failures), drivers prepared for the failure event sooner than when they could see why the automation was failing (i.e. predictable failures).This finding should be further explored to understand if this is consistently the case. As early preparation for a failure event has a significant impact on the driver's takeover quality, a training program event should be developed to encourage drivers to monitor and prepare for a takeover as soon as a takeover request is prompted, or the reliability goes below its threshold. This may also be indicative of a need to design displays that create a sense of urgency and prompt drivers to prepare for a failure event as soon as the request is issued, regardless of the failure type that participants may experience.

An additional contribution from this research was the covariate analysis that clearly indicated that regardless of failure type, preparing for a failure event, or taking over prior to a failure event significantly improves the driver's takeover quality, as opposed to taking over after a failure event. These results show that it is necessary to design the automated systems for cars to encourage early preparation and takeover in drivers.

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Appendix A: Recruitment Materials

Participants Needed!

For a high-fidelity driving simulator study on driving behaviour

Requirements:

- Can read and speak English
- Have a G drivers license or equivalent
- Be between the ages of 25- 30

Human Factors & Applied Statistics Lab

Mechanical & Industrial Engineering UNIVERSITY OF TORONTO

Location: Rosebrugh Building (RS) 164 College St.

Duration: ~3 hours

Compensation: $14/hr + up to $8 bonus

To get started, fill out this short screening questionnaire:

https://goo.gl/R2U5DG

For more information, contact the researcher at

drivingsimulatorstudy@gmail.com

Figure 26: Recruitment Poster

Online Message Board Posts for Kijiji, Craigslist, Facebook job recruitment groups and listservs:

*Paid $ Participants Needed for Driving Simulator Study at U of T** - $14

University, Toronto, Ontario

The University of Toronto is trying to study how people interact with automated vehicles. The goal of this research is to make our roads safer through understanding driving behaviors under specific situations. If you are eligible, you will be invited to our laboratory to drive in our high-fidelity driving simulator.

You may be eligible to participate if you are:

-Age 25-30

-Can read and speak English

-Have a G drivers license or equivalent

Compensation: $14/hr + up to $8 bonus

To get started, fill out this short screening questionnaire:

http://ca.surveygizmo.com/s3/50017337/Screening-Questionnaire-Automation

Or contact me at drivingsimulatorstudy@gmail.com

University of Toronto Driving Simulation Experiment – Availability Inquiry

Dear__________,

Thank you for your interest in the driving simulator experiment at the University of Toronto. You are eligible to participate in our experiment.

Please follow the doodle link (https://doodle.com/poll/5dtkyibrrt62qabu) and pick a date and time that you would like to do the experiment. The experiment is expected to take less than 3 hours. If none of the potential time slots in this period work for you, please contact me directly at Samantha.hopkins@mail.utoronto.ca, and I will make the necessary arrangements.

Once you fill out the Doodle poll, and appointment confirmation email will be sent to you along with additional details about the experiment.

I am providing you with a copy of the consent form so you can familiarize yourself with what you will be expected to do during the experiment.

Thank you again for your participation in the survey. If you have any questions about the experiment, please feel free to contact me.

All the best,

Samantha Hopkins, MASc Candidate
Mechanical and Industrial Engineering
Human Factors and Applied Statistics Lab
University of Toronto

Confirmation Email:

Dear ________,

Thank you for filling out the doodle poll. This email is to **confirm** that you will be participating in the driving simulator experiment on **____, ____ __th from __-__am/pm.**

Please reply back to this email letting me know that this time still works for you. If not, we can arrange another time.

When you come in for the experiment, please meet me at the Rosebrugh building, which is located at 164 College Street in room 313.

Regarding the experiment, if possible, please don't wear any eye makeup. This will help us when we calibrate the eye tracker.

I look forward to hearing back from you.

All the best,
Samantha

Appendix B: Screening Questionnaire

University of Toronto,

Human Factors and Applied Statistics Lab

Driving Experiment Eligibility Questionnaire

You are invited to participate in a driving simulator research conducted by the Human Factors and Applied Statistics Lab (Director: Prof. Birsen Donmez) at the University of Toronto.
The goal of this research is to make our roads safer by understanding driver behaviors under specific situations. The following questionnaire will help us assess your eligibility for the study. If you are eligible, you will be invited to our laboratory.
Please note that all information collected will be held in the strictest confidentiality. Personal data will be stored securely in the Human Factors and Applied Statistics Lab's secure password-protected Network Attached Storage at the University of Toronto. Under no circumstances will personal data be revealed to any third party, for any purpose. If you are not chosen for this experiment and do not want to be informed for future driving study in our lab, your information will be deleted.
Please note that personal contact information will be used solely for the purpose of future research opportunities at our lab, if you so desire.
If you have any questions or concerns you would like to be addressed before or after completing this questionnaire, please contact the investigator at drivingsimulatorstudy@gmail.com
Would you like to continue with this questionnaire?

Yes/ No

1. What is your first name? ________________________
2. What is your last name? ________________________
3. What is your age? ___________________
4. What is your gender?
   a. Male
   b. Female
   c. Other
   d. Prefer not to answer
5. Your email address: ________________________
6. Your phone number: ________________________
7. Your preference on the method of contact:
   email / phone / both

8. If you are interested in participating in future research at the Human Factors and Applied Statistics Lab, please indicate below (if you are not interested, you can skip this question).

I am interested in participating in your future research; please contact me when opportunities become available.

Simulator Sickness Screening

Some people tend to experience a type of motion sickness, called simulator sickness, when driving the simulator. The next questions can help us identify if you might be prone to simulator sickness.

7. Have you ever driven in a driving simulator before?
   a. No, never
   b. Once or twice
   c. Multiple times
   d. Regularly
8. (logic: only when "No, never" was not chosen in last question.) If you have used a driving simulator before, did you experience simulator sickness?
   a. Yes
   b. No
9. Do you frequently experience migraine headaches?
   a. Yes
   b. No
10. Do you experience motion sickness?
   a. Yes
   b. No
11. Do you experience claustrophobia?
   a. Yes
   b. No
12. Are you pregnant?
   a. Yes
   b. No

Driver Survey

Please fill in the blanks or choose the best one(s) unless otherwise noted.

1. Do you ordinarily wear corrective lenses (e.g., glasses) of any kind?
   a. Yes
   b. No
2. (Logic: only shows when "Yes" is chosen in last question) If you do have corrected vision, are you able to wear contact lenses during the experiment?
   a. Yes
   b. No
3. Are you right handed?
   a. Yes
   b. No

4. Are you proficient in reading and understanding English?

   a. Yes

   b. No

5. What is your current driver's license?
   a. G license in Ontario or full license in the U.S.
   b. G2 license in Ontario or equivalent in the U.S.
   c. G1 licenses in Ontario or equivalent in the U.S.
   d. I don't have a driver's license
   e. Other licenses (please specify)

6. When did you pass your FIRST road test and obtain corresponding driver's license (e.g., G2 license in ON, Canada or equivalent)? (MM / YYYY)?

____

7. When did you obtain your FIRST full driver's license, if you have it? (MM / YYYY)

____

8. What type of motor vehicle do you drive most often?
   a. Passenger car
   b. Pick-up truck
   c. Cargo van
   d. Box/Delivery truck
   e. Bus, tractor trailer, vehicle with more than 2 axles
   f. Other, please specify

9. What are your primary reasons for driving in a typical week (you can select multiple responses)?

   a. Commuting

   b. Business

   c. Shopping

   d. Social

   e. Recreational

   f. Other, please specify

10. (Logic: only when "a" is chosen in last question) If you drive for commuting, please specify your one-way distance:

   a. under 10km

   b. 10km to 20km

   c. 20km to 30km

   d. Above 30km

11. How often do you drive a car or other motor vehicle?
   a. Almost every day
   b. A few days a week
   c. A few days a month
   d. A few times a year or less
   e. Never

12. Over the past 1 year, how many kilometers did you drive?

a. Under 10,000 km
b. Between 10,001 km and 20,000 km
c. Between 20,001 km and 30,000 km
d. Between 30,001 km to 40,000 km
e. Between 40,001 km to 50,000 km
f. Over 50,001km
g. None

Vehicle Automation Screening Questionnaire

<u>Question 1:</u>

Please read through the description of the Cruise Control (CC) system carefully before you proceed to the questions.

* **Cruise Control**:

- <u>What it does</u>: The system maintains a constant vehicle speed that is set by the driver.
- <u>How it works</u>: The system automatically controls the acceleration to increase or decrease the gas inputted into the engine to maintain the driver's set speed.
- <u>Limitation(s)</u>: The system does not slow down the car when there is a need (e.g., traffic ahead).

1. Before reading the description above, how much did you know about cruise control?

- I never heard about it
- I heard about it but did NOT know what it does
- I knew what it does, but did NOT know how it worked
- I knew what it does and how it works, but did NOT know its limitations
- I knew what it does, how it works, and its limitations

2. Have you ever used this system?

- Yes
- No

3. (logic: if answer is "yes" in question 2.) How often have you used it?

- Less than once a year
- Several times a year
- Several times a month
- Several times a week
- Almost every day

4. Do you own or frequently drive a car equipped with this system?

- Yes
- No

5. (logic: if "Yes" in question 4 and "Yes" in question 2) Have you ever used this system equipped on your car or the car you frequently drive?

- Yes
- No

6. (logic: "No" is given in question 5 and "Yes" is given in question 4.) Why haven't you used this system in your own vehicle? (Check all that apply)

- I don't know how to use it
- It is too complicated to use (too many steps to activate or deactivate it)
- The instructions make no sense
- I don't trust it
- I tried it a few times and I felt unsafe
- Other: _____

7. (Logic: if "Yes" in question 2) Have you ever been involved in any accidents while using this system?

- Never
- Once
- 2-3 times
- More than 3 times

<u>Question 2:</u>

Please read through the description of the Adaptive Cruise Control (ACC) system carefully before you proceed to the questions.

* **Adaptive Cruise Control**:

- <u>What it does</u>: the system functions like cruise control, however, it is more advanced as it also automatically adjusts the vehicle speed to maintain a safe distance from a leading vehicle.
- <u>How it works</u>: the system uses radar equipped in front of the vehicle to detect the distance to a leading vehicle. It controls the acceleration similar to cruise control to maintain a set speed, but also decelerates if the leading vehicle slows down.
- <u>Limitation(s):</u> the automation is imperfect, and may not work properly in poor weather conditions and does not detect stationary objects (e.g., a stopped vehicle). Additionally, depending on the specific system, the system may not be able to apply the full braking force to bring the vehicle to a complete stop or slow the vehicle down enough to maintain a safe distance to the vehicle ahead.

1. Before reading the description above, how much did you know about Adaptive Cruise Control ?

- I never heard about it
- I heard about it but did NOT know what it does
- I knew what it does, but did NOT know how it worked
- I knew what it does and how it works, but did NOT know its limitations
- I knew what it does, how it works, and its limitations

2. Have you ever used this system?

- Yes
- No

3. (logic: if answer is "yes" in question 2.) How often have you used it?

- Less than once a year
- Several times a year
- Several times a month
- Several times a week
- Almost every day

4. Do you own or frequently drive a car equipped with this system?

- Yes
- No

5. (logic: if “Yes” in question 4 and “Yes” in question 2) Have you ever used this system equipped on your car or the car you frequently drive?

- Yes
- No

6. (logic: “No” is given in question 5 and “Yes” is given in question 4.) Why haven’t you used this system in your own vehicle? (Check all that apply)

- I don’t know how to use it
- It is too complicated to use (too many steps to activate or deactivate it)
- The instructions make no sense
- I don’t trust it
- I tried it a few times and I felt unsafe
- Other: _____

7. (Logic: if “Yes” in question 2) Have you ever been involved in any accidents while using this system?

- Never
- Once
- 2-3 times
- More than 3 times

Question 3:

Please read through the description of the Lane Departure Warning (LDW) system carefully before you proceed to the questions.

* **Lane Departure Warning**:

- What it does: the system is designed to warn drivers when the vehicle begins to move out of its lane (unless a turn signal is on in that direction) on freeways and arterial roads.
- How it works: this system uses a camera to recognize the lane markings on the road and the boundaries of the lanes.
- Limitation(s): this warning system is imperfect and may not work properly when the lane markings are not clearly visible, e.g. poor weather or road conditions. Additionally, this system is not always accurate, and may provide false alarms.

1. Before reading the description above, how much did you know about Lane Departure Warning?

- I never heard about it
- I heard about it but did NOT know what it does
- I knew what it does, but did NOT know how it worked
- I knew what it does and how it works, but did NOT know its limitations
- I knew what it does, how it works, and its limitations

2. Have you ever used this system?

- Yes
- No

3. (logic: if answer is “yes” in question 2.) How often have you used it?

- Less than once a year
- Several times a year

- Several times a month
- Several times a week
- Almost every day

4. Do you own or frequently drive a car equipped with this system?

- Yes
- No

5. (logic: if "Yes" in question 4 and "Yes" in question 2) Have you ever used this system equipped on your car or the car you frequently drive?

- Yes
- No

6. (logic: "No" is given in question 5 and "Yes" is given in question 4.) Why haven't you used this system in your own vehicle? (Check all that apply)

- I don't know how to use it
- It is too complicated to use (too many steps to activate or deactivate it)
- The instructions make no sense
- I don't trust it
- I tried it a few times and I felt unsafe
- Other: _____

7. (Logic: if "Yes" in question 2) Have you ever been involved in any accidents while using this system?

- Never
- Once
- 2-3 times
- More than 3 times

Question 4:

Please read through the description of the Lane Keeping Assist (LKA) system carefully before you proceed to the questions.

* **Lane Keeping Assist**:

- What it does: the system is designed to steer the vehicle to keep it centered in the lane.
- How it works: this system uses a camera to recognize the lane markings on the road and the boundaries of the lane, and based on that information, it continuously steers the car.
- Limitation(s): the use of this system is limited to highway driving. It may not work properly when the lane markings are not clearly visible (e.g. poor weather or road conditions), or when driving around sharp curves.

1. Before reading the description above, how much did you know about Lane Keeping Assist?

- I never heard about it
- I heard about it but did NOT know what it does
- I knew what it does, but did NOT know how it worked
- I knew what it does and how it works, but did NOT know its limitations
- I knew what it does, how it works, and its limitations

2. Have you ever used this system?

- Yes

- No

3. (logic: if answer is “yes” in question 2.) How often have you used it?

- Less than once a year
- Several times a year
- Several times a month
- Several times a week
- Almost every day

4. Do you own or frequently drive a car equipped with this system?

- Yes
- No

5. (logic: if “Yes” in question 4 and “Yes” in question 2) Have you ever used this system equipped on your car or the car you frequently drive?

- Yes
- No

6. (logic: “No” is given in question 5 and “Yes” is given in question 4.) Why haven’t you used this system in your own vehicle? (Check all that apply)

- I don’t know how to use it
- It is too complicated to use (too many steps to activate or deactivate it)
- The instructions make no sense
- I don’t trust it
- I tried it a few times and I felt unsafe
- Other: _____

7. (Logic: if “Yes” in question 2) Have you ever been involved in any accidents while using this system?

- Never
- Once
- 2-3 times
- More than 3 times

Thank you for taking our survey. Your response is very important to us. We will contact if you are eligible for our experiment.

Appendix C: Counterbalanced Design

The table below shows the order of the drives that each participant performed

P=Predictable Failure Scenario

U=Unpredictable Failure Scenario

								Male Participant #	Female Participant #
Group 1	1	Baseline	P	U	TOR	P	U	P06, P28	P09, P32
	2	Baseline	U	P	TOR	P	U	P07	P39
	3	Baseline	P	U	TOR	U	P	P08	P41
	4	Baseline	U	P	TOR	U	P	P10, P29	P31
	5	TOR	P	U	Baseline	P	U	P11	P36
	6	TOR	U	P	Baseline	P	U	P26	P21
	7	TOR	P	U	Baseline	U	P	P13	P17
	8	TOR	U	P	Baseline	U	P	P18, P37	P15

Group 2	1	Baseline	P	U	Reliability	P	U	P25	P33
	2	Baseline	U	P	Reliability	P	U	P12	P30
	3	Baseline	P	U	Reliability	U	P	P20	P24
	4	Baseline	U	P	Reliability	U	P	P23	P38
	5	Reliability	P	U	Baseline	P	U	P19	P16
	6	Reliability	U	P	Baseline	P	U	P22	P40
	7	Reliability	P	U	Baseline	U	P	P14	P35
	8	Reliability	U	P	Baseline	U	P	P27	P34, P42

Appendix D: Why the second failure is not included in the data analysis

The second failure in each drive is not included in most of the data analysis because of the inherent differences in the design of the second predictable failure. As that failure could not be included, in order to exclude data that could be influenced by a participant's learning curve, the second unpredictable failure was not analyzed for most of the data as well (except where otherwise indicated).

<u>Design of the second predictable failure:</u>

Given the limitations in designing a road path with two T-intersections on the same side of the street, the second predictable failure occurred at a T-intersection, where the new road was on the left side (Figure 27). When the car failed, the car would move in the zig-zag manner shown in red in Figure 27. The impact of the difference in how the second predictable failure progressed as compared to the first predictable failure and the unpredictable failures was unclear at the time of the design, even with extensive pilot testing. However, it became clear during data collection that participants were not able to predict the second predictable failure, as they assumed that vehicle sensors looked at the lines on either side of the vehicle, rather than the entire road. Additionally, the manner in which the car failed was very different from the rest of the failures (see the vehicle path in Figure 27, as compared to the vehicle only veering to the right) which surprised the participants. Analysis of the data at the end of experimentation (see below) confirmed that the second predictable failure was inherently different from the other failures that the participant experienced, and thus could not be included in the data.

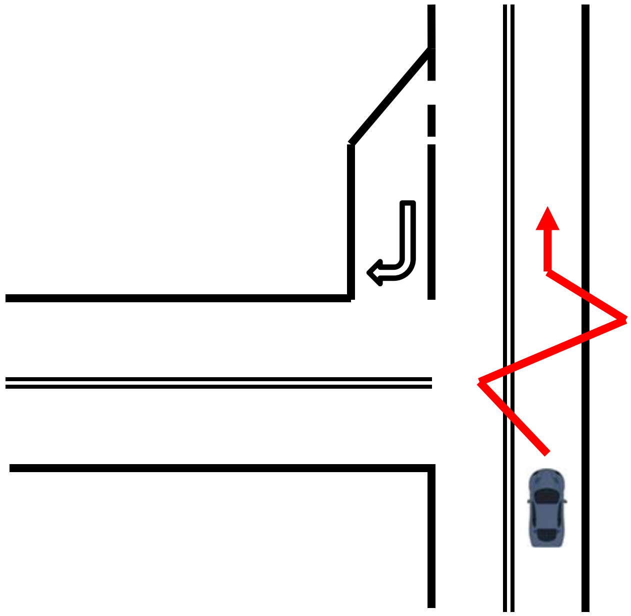


Figure 27: The intersection for the second predictable failure, including the vehicle's path

<u>Analysis of the failures</u>

When performing the preliminary analysis of the impact of failure type on a participant's takeover, an anomaly in the acceleration data was discovered. Specifically, the recorded maximum accelerations that were recorded did not corroborate with the reaction time. This indicated that it was possible that the accelerations that were recorded during the predictable failure events were the accelerations of the simulator acting upon the vehicle, rather than the driver's reaction to the failure event. Analysis determined that while this was the case for the predictable failures, there was a significant difference between the accelerations experienced between the first and second predictable failure, and there given that the second predictable failure had a greater level of urgency associated with it than the first one (the car failed in a zig-zag manner, rather than going to the right), it was removed from the analysis. In order to combat the impact possible learning effects from the second unpredictable failure, that too was removed from most of the analysis.

The analysis below also shows that the original measures of acceleration were not possible to use in the analysis because of the manner in which they were calculated. The contrasts for this analysis are explained in Appendix J.

The analysis that led to the above conclusion is below:

<u>Additional dependent measures were defined</u>:

- Maximum Acceleration (m/s^2)
    - Maximum acceleration is defined as the maximum vehicle acceleration in the X-Y axis during a failure event (from 10 seconds before the failure to 20 seconds after the failure). The variable is calculated as follows (Gold et al., 2013):
        - $a_c = \sqrt{a_{long}^2 + a_{lat}^2}$
- Angular Acceleration (degrees/s)
    - Maximum angular velocity is calculated during a failure event similar to maximum acceleration, i.e., from 10 seconds before the failure to 20 seconds after the failure.

<u>Analysis of the impact of failure type on takeover:</u>

In order to examine the impact of failure type on a participant's takeover quality, results from contrast A are reviewed. In this contrast, only baseline drives are reviewed in order to remove the impact of the displays on a participant's takeover response. These results are located in Table 35.

As seen in Table 35, participants put their hands on the wheel, and take over control from the automation significantly sooner when they experience a predictable failure than when they experience an unpredictable failures. This indicates that participants likely were more prepared to react to an impending failure when it was predictable than when it was unpredictable.

Table 35: Effect of failure type on takeover

	Estimate	t-Value	p-Value	Lower	Upper
Hands-On-Wheel Time (s)	-1.51	t(34)=-5.73	<.0001	-2.04	-0.97
Take-Over Time (s)	-1.04	t(34)=-7.80	<.0001	-1.31	-0.77
Maximum Acceleration (log, m/s^2)	0.49	t(32)=4.19	0.0002	0.25	0.73
Angular Velocity (log, degrees/s)	0.81	t(32)=5.54	<.0001	0.51	1.1

However, the results for the maximum acceleration (see Figure 28) and angular velocity do not corroborate with the participant's supposed preparation for a predictable failure versus an unpredictable failure, as these results show an increase in acceleration and angular velocity when participants experience a predictable failure. Given that there was no significant effect between predictable and unpredictable failures for the angle range or the maximum angle (both of which specifically measure the driver's input to the steering wheel during a takeover maneuver), a possible explanation for this discrepancy is that the simulator-caused accelerations that the ego-vehicle experienced at each takeover event could have been greater for the predictable failures than for the unpredictable failures. Another possible explanation is that, as explained earlier, the two different predictable failures had a different level of urgency and predictability, and participants may have reacted significantly differently at the second predictable failure than at the first predictable failure, thus impacting the statistics of the results.

In order to understand this inconsistency, further analysis was performed by separating each of the failures. The first failure in a drive where participants experienced predictable failures was called P1, and the second failure was called P2. The first failure in a drive where participants experienced unpredictable failures was called U1, and the second failure was called U2. The contrasts used in this analysis are shown in Appendix B.

The results of the analysis are below:

Table 36: Difference between P1 and P2

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Acceleration (m/s^2)	-3.31	t(34)=-10.30	<.0001	-3.96	-2.66
Angular Velocity (degrees/s)	-17.31	t(34)=-17.36	<.0001	-19.34	-15.29
Hands-On-Wheel Time (s)	-1.81	t(34)=-3.76	0.0006	-2.79	-0.83
Angle Range (degrees)	8.86	t(34)=3.91	0.0004	4.25	13.46
Maximum Angle (degrees)	8.39	t(34)=5.02	<.0001	4.99	11.79
Standard deviation of steering (degrees)	2.12	t(34)6.97	<.0001	1.5	2.74

As seen in Table 36, there is a significant difference between P1 and P2. The maximum acceleration in P1 is significantly less than the acceleration in P2, however, the maximum angle and angle range were significantly greater in P1 than in P2. If the maximum acceleration in Table 35 was due to driver's taking over control from the automation, then the results for the maximum acceleration and the maximum angle would correlate. However, they are not, and this means that the maximum accelerations that are measured in the predictable failures are caused by the manner in which the simulator creates the predictable failure situations, and therefore are the maximum experienced accelerations by the ego-vehicle. As the maximum accelerations and angular velocities are significantly different, the level of urgency that a participant experiences in each of the predictable failures is different.

The hands on wheel time was significantly lower for P1 than P2, however the take-over time between the two is not significant, which shows that participants aware of an impending take-over sooner at P1 than P2, but did not take-over until the vehicle failed. The standard deviation of the steering wheel angle was significantly greater for P1 than P2, which means that it is possible that the driving performance was better after P2 than P1 (Shen), but it also suggests that the driver exerted more effort to keep the vehicle positioned in the center of the road (Erikson). A possible reason for this is the nature of the failure—for

P1, if a failure occurred, the vehicle went into the right lane, while for P2, the vehicle moved in a zigzag pattern, and the participant may have already closer to the center of the lane when they were taking over control. Again, this shows that P1 and P2 are not commensurate, and when investigating the impact of failure type, it is necessary to separate them from each other for analysis.

Table 37: Difference between P1 and U1

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Acceleration (m/s^2)	1.02	t(34)=5.58	<.0001	0.65	1.4
Angular Velocity (degrees/s)	3.78	t(34)=7.88	<.0001	2.81	4.76
Hands-On-Wheel Time (s)	-1.87	t(34)=-4.44	<.0001	-2.72	-1.01
Take-Over Time (s)	-1.2	t(34)=-7.48	<.0001	-1.52	-0.87
Standard deviation of steering (degrees)	1.07	t(34)=4.19	0.0002	0.55	1.6

As seen in Table 37, the maximum acceleration is greater in P1 than in U1. As the maximum angle and the angle range were not significant, it is very likely that the maximum acceleration and angular velocity were those acted upon the vehicle at the takeover situation, rather than the accelerations from the driver. Another possibility is that because the car went into the turning lane for P1, there may have been a greater sense of urgency on the part of the driver to bring the car back into the original lane prior to the intersection (when taught to drive, driver's are told that they should not switch lanes at an intersection), or simply to follow the lead vehicle, because they are concerned that the automation may make them turn at the intersection. For U1, the car simply left the lane and went onto the shoulder where it eventually hit the rumble strip. There was no concern for the path of the car. For this possibility, the maximum angle and angle range may not be significant because the same amount of steering wheel movement was required to get the car back on the road after the failure situation. The fact that the standard deviation of the steering wheel angle was greater for P1 than for P2 supports this analysis, because the different nature of the predictable failure, participants exerted more effort for their steering corrections at the intersection than at the unpredictable failures.

Most of the results from Table 37 corroborate with the results from Table 38, which makes sense because the unpredictable failures occur in the same manner. However, the angle range and maximum angle are greater for P1 than U2, which may indicate some learning occurred at U2, and participants were more aware of the possibility of a failure occurring, and therefore may have more smoothly brought the vehicle back to the center of the lane.

However, given that the hands on wheel time and the takeover time were sooner for the intersection than the unpredictable failure, it is likely that the greater accelerations, angular velocity and angle range are due to the manner in which the failure occurred, and how the simulator moved the vehicle out of the lane for P1.

The standard deviation of the steering wheel angle, however, is lower in the comparison between P1 and U2 than P1 and U1. The reason for this is unclear, but it may be due to the curvature in the road subsequent to U2, that was not present subsequent to U1.

Table 38: Difference between P1 and U2

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Acceleration (m/s^2)	1.14	t(34)=5.54	<.0001	0.72	1.55
Angular Velocity (degrees/s)	3.62	t(34)=6.19	<.0001	2.43	4.81
Hands-On-Wheel Time (s)	-1.96	t(34)=-6.94	<.0001	-2.53	-1.38
Take-Over Time (s)	-1.16	t(34)=-6.17	<.0001	-1.54	-0.78
Angle Range (degrees)	4.15	t(34)=2.43	0.02	0.68	7.62
Maximum Angle (degrees)	3.8	t(34)=2.91	0.006	1.15	6.46
Standard deviation of steering (degrees)	0.51	t(34)=1.9	0.066	-0.035	1.05

Table 39 and Table 40 show very similar results between P2 and both unpredictable failures. Given that the angle range and maximum angle for P2 is significantly less than for U1 and U2, and yet the maximum acceleration and angular velocity are significantly greater for P2, that shows that the accelerations experienced at P2 are those from the simulator moving the vehicle, rather than the driver.

Table 39: Difference between P2 and U1

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Acceleration (m/s^2)	4.34	t(34)=12.25	<.0001	3.62	5.16
Angular Velocity (degrees/s)	21.1	t(34)=20.29	<.0001	18.99	23.21
Take-Over Time (s)	-0.89	t(34)=-2.70	0.011	-1.57	-0.22
Angle Range (degrees)	-6.26	t(34)=-3.05	0.004	-10.43	-2.08
Maximum Angle (degrees)	-6.47	t(34)=-4.25	0.0002	-9.57	-3.38
Standard deviation of steering (degrees)	-1.05	t(34)=-4.13	0.0002	-1.56	-0.53

Table 40: Difference between P2 and U2

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Acceleration (m/s^2)	4.45	t(34)=13.91	<.0001	3.8	5.1
Angular Velocity (degrees/s)	20.94	t(34)=20.29	<.0001	18.99	23.21
Take-Over Time (s)	-0.86	t(34)=-2.43	0.02	-1.57	-0.14
Angle Range (degrees)	-4.7	t(34)=-2.81	0.008	-8.1	-1.3
Maximum Angle (degrees)	-4.59	t(34)=-3.79	0.0006	-7.05	-2.13
Standard deviation of steering (degrees)	-1.61	t(34)=-7.53	<.0001	-2.05	-1.18

Table 41: Difference between U1 and U2

	Estimate	t-Value	p-Value	Lower	Upper
Maximum Angle (degrees)	1.89	t(34)=2.04	0.049	0.009	3.76
Standard deviation of steering (degrees)	-0.57	t(34)=-7.53	<.0001	-2.05	-1.18

Table 41 shows a slight difference between U1 and U2. A possible reason for this difference is the learning associated with the order of experiencing these failures. The maximum angle may be significantly larger for U1 than U2 because the participant realizes that the failure will not lead to severe negative repercussions and thus has a more smooth take over, and transition back into the lane at U2. The fact that the standard deviation of the steering is less for U1 than U2 does not go against this idea, because again, there was a curve that was within the 20 second time period subsequent to the takeover, and that may have an impact on the participant's driving quality, as there was a higher effort to maintain the vehicle position on the curve than on a straight road.

Given the above analysis, a new manner to calculate the maximum acceleration was devised, in order to only look at the accelerations inputted by the driver, rather than using the maximum acceleration from the entire failure scenario, which would include the accelerations acted upon the vehicle from the simulator.

mean	**3.3**	**1.1**	**2.6**	**1.1**	**3.9**	**2.6**	**2.6**	**1.5**
S.D.	1.2	0.77	0.6	0.55	0.96	1.5	0.71	0.66

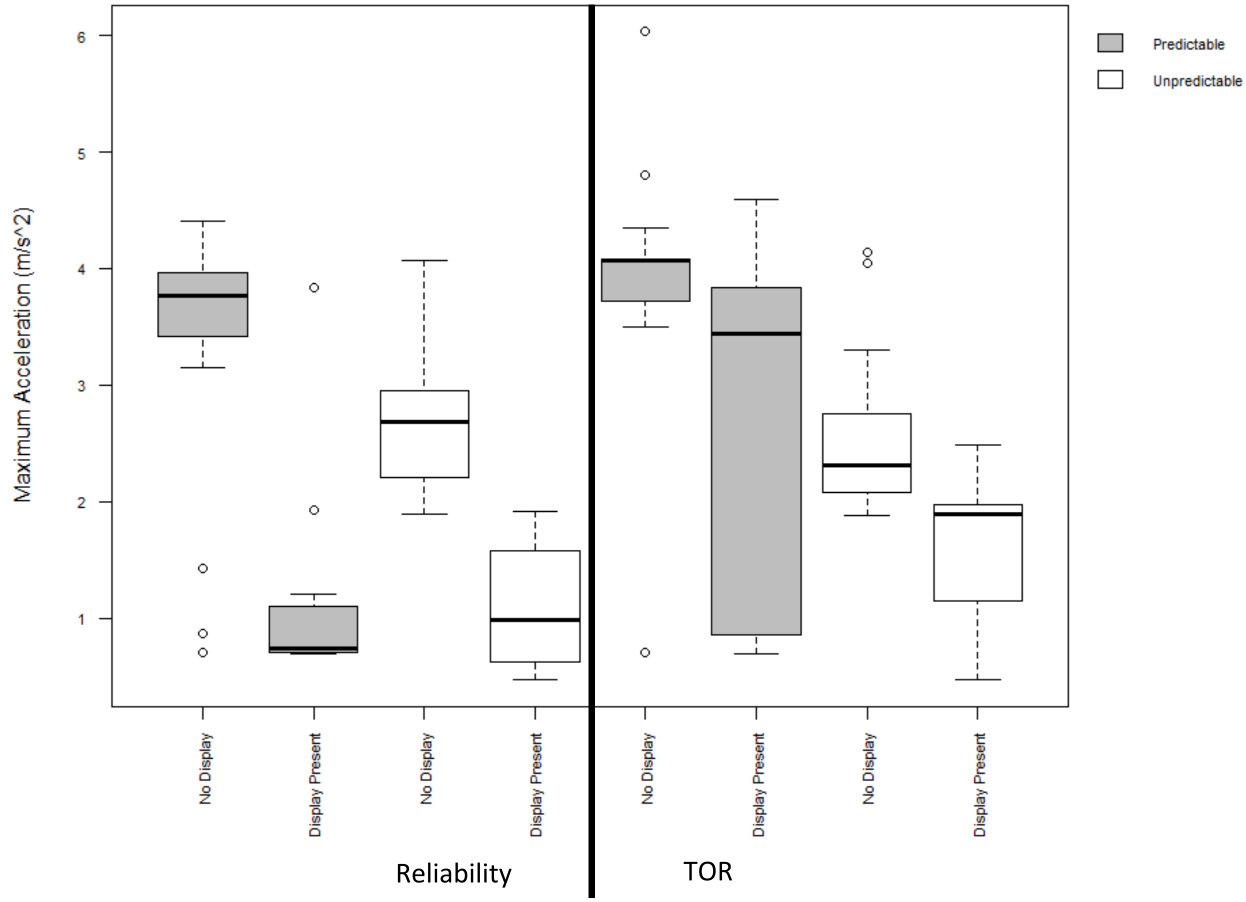


Figure 28: Boxplot of the raw data for the Maximum Acceleration

Appendix E: Presentation to Participant

The slides that were used for the presentation for each participant are shown below.

Automation Orientation

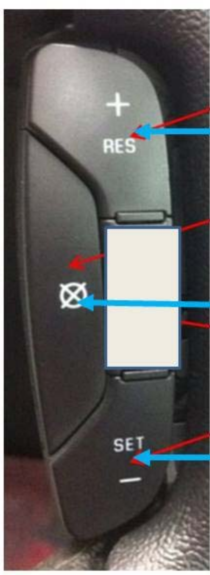
1

ACC Display

2

3

Using the ACC



Reset or Increase the set speed.

Cancel the ACC

Set or Decrease the set speed

Notes:
- Can <u>brake</u> to <u>cancel</u> the ACC too.
- Once the ACC is set, <u>remove</u> your foot from the accelerator

4

ACC Ready

5

Limitations

- Only has 30 % braking power (cannot come to an abrupt full stop
- Does not work well in poor weather
- Does not detect pedestrians, motorcycles , small objects or stationary objects on the road

- Seemingly random failures can occur due to sensor or algorithmic failures

6

Quick Quiz!

- Stationary objects on the road

7

Quick Quiz!

- Poor weather

8

Quick Quiz!

• Pedestrians on the road

9

LK Display

10

Lane Keeping display

11

Usage of LK

Engage and Disengage the LK

- **Notes:**
- Turn steering wheel 6° from the center in either direction to disengage the LK
- The LK will not engage if the steering wheel is more than 6° off center
- You can engage the LK at any point on the road. Essentially, if it can steer there, then you can engage it there.

12

About driving with LK

- Can have your hands near the wheel or completely off the wheel.
- When they are on the wheel, that means that you are going to disengage the automation

13

Limitations

- The system must "see" the lane markings therefore it may not function properly if:
  - The visibility or the weather is poor
  - The lane markings aren't clearly marked– either they are excessively worn, or adjusted due to construction
  - The lane markings quickly change– possibly due to construction or intersections
- Seemingly random failures can occur due to sensor or algorithmic failures

14

Quick Quiz!

- The lane markings change quickly due to an intersection

15

Quick Quiz!

- Lanes are adjusted due to construction

16

Quick Quiz!

- Visibility is poor

17

Secondary Task

- Target Phrase: **“Discover Project Missions”**
- Lose $0.40 for each incorrect answer
- Earn $0.20 for each correct answer
- Driving performance will also be observed and rated
- Max bonus is $8

18

Practice Drive

- Please drive with the ACC and LK. Please engage in the secondary task.
- Turn the ACC and LK off and on

19

How do you feel?

- Any simulator sickness?

20

Rules for the drives

- Follow the red car in front of you
- The speed limit is 50 mph
- Wait until told to turn the automation <u>on</u> at the beginning of the drive
- If you turn <u>off</u> the automation (either LK or ACC), please wait until told to turn it back <u>on</u>, by either the computer or experimenter

21

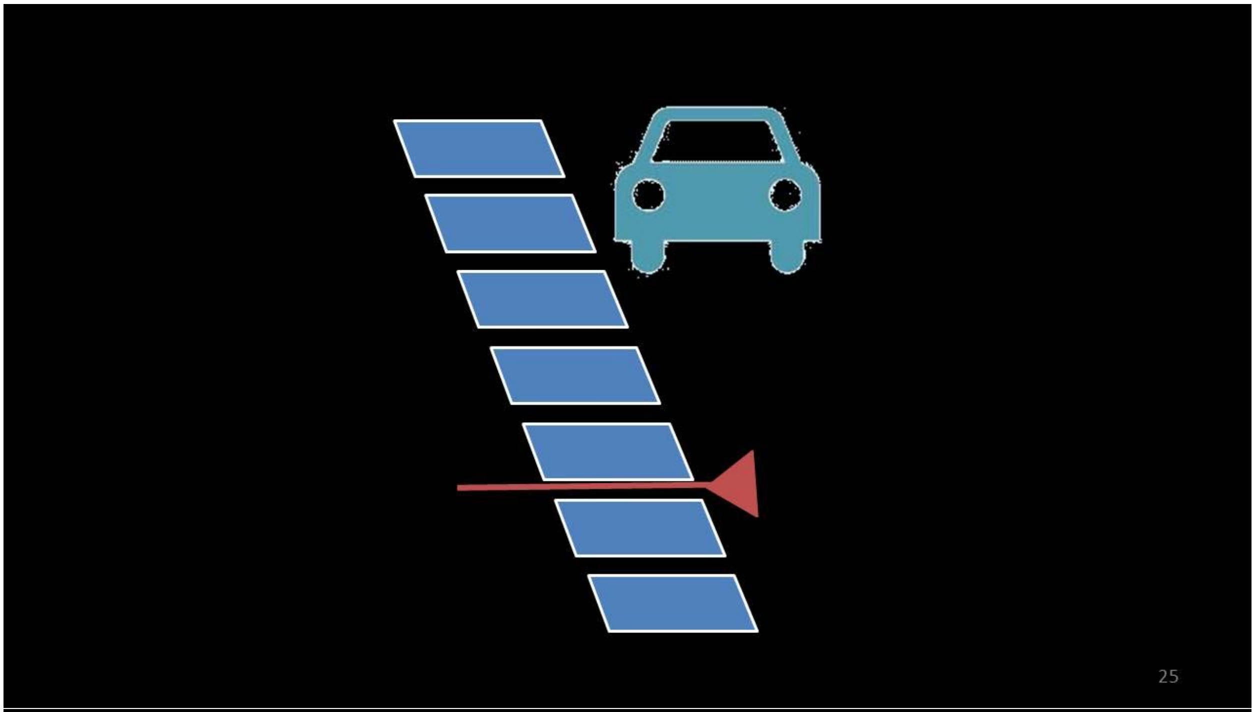
TOR Display Orientation

22

23

Reliability Display Orientation

24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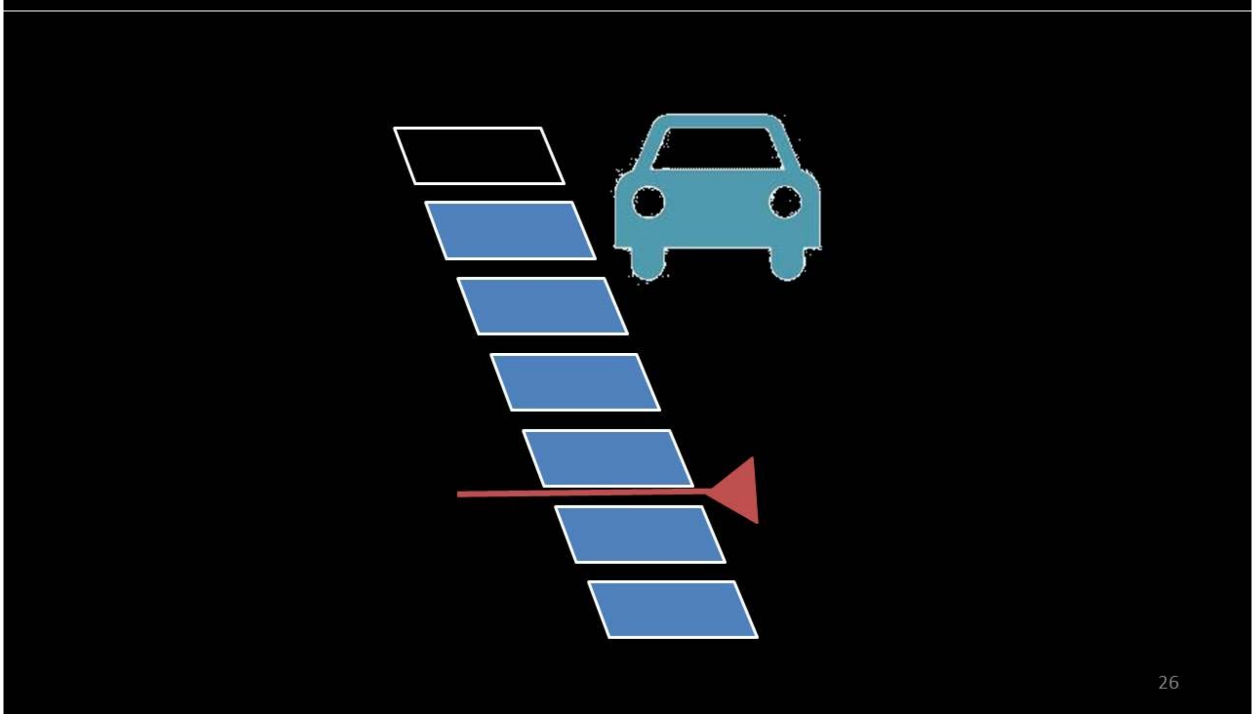
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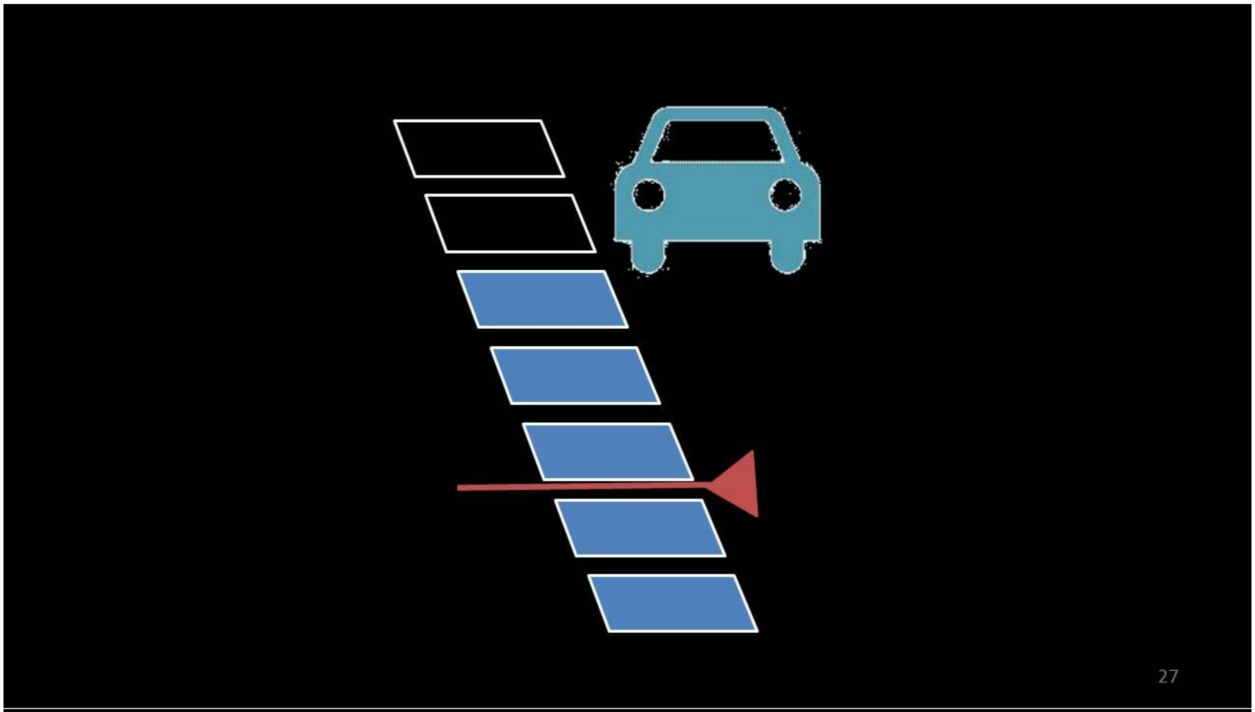
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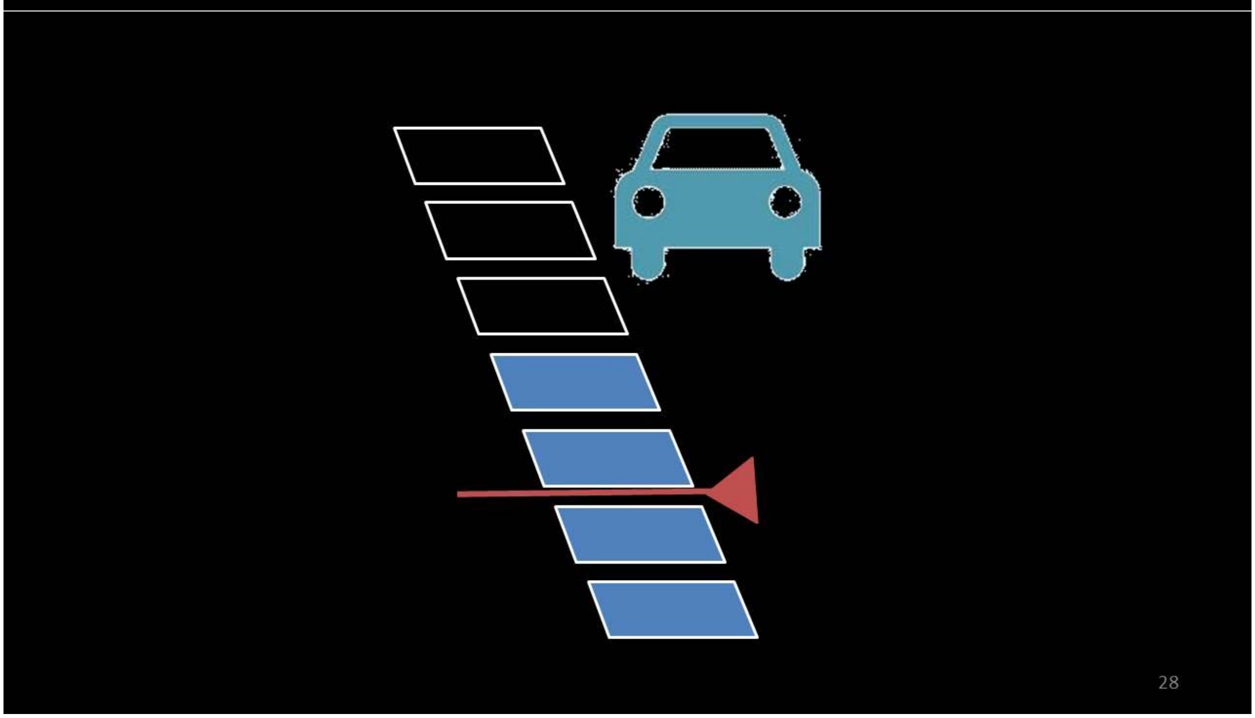
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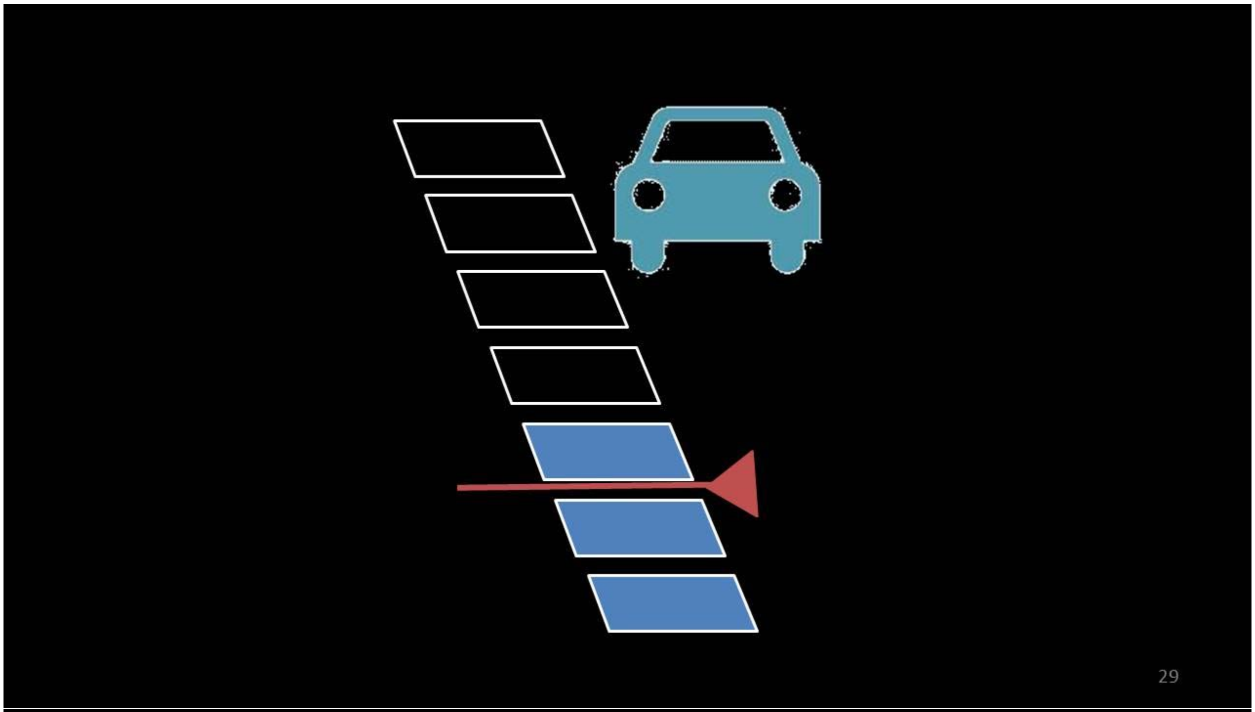
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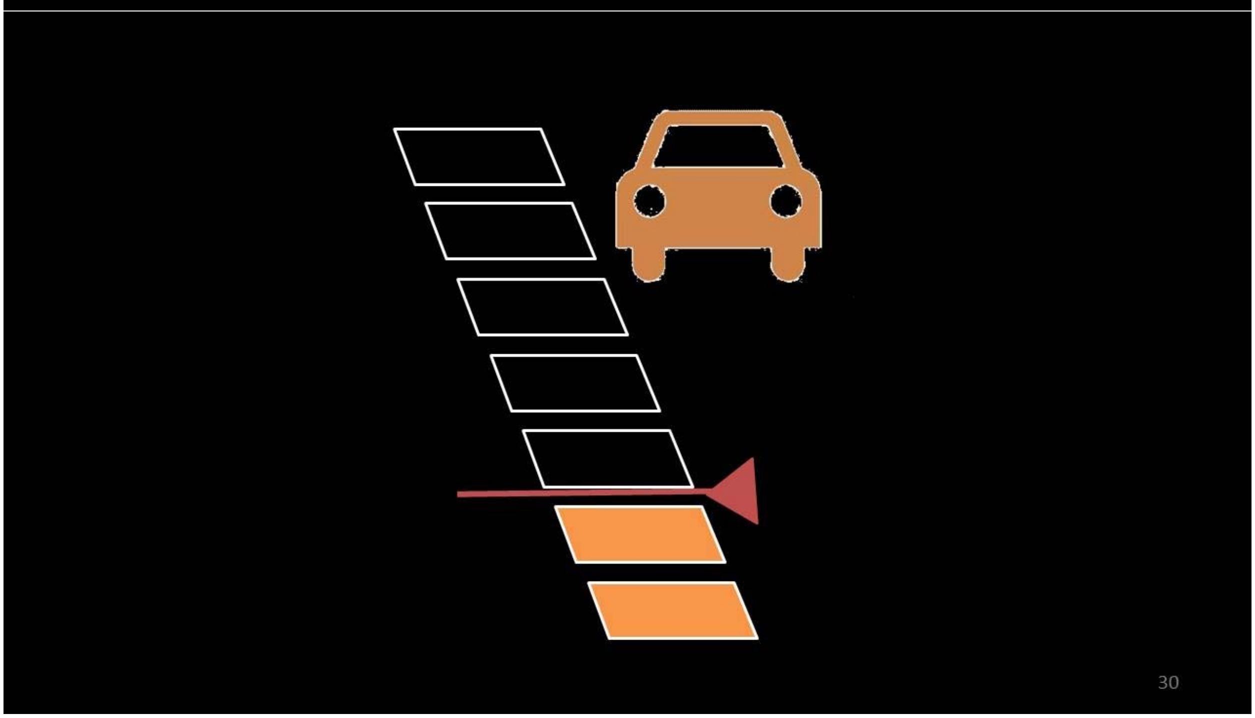
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Appendix F: Informed Consent

Mechanical & Industrial Engineering
UNIVERSITY OF TORONTO

Human Factors
& Applied Statistics Lab

Participant Consent Form

Version 4/23/2018

Title: Simulator experiment on automated driving behavior

Investigators: **Prof. Birsen Donmez, PhD PEng | Associate Professor**
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Ms. Samantha Hopkins, MASc Candidate
Department of Mechanical & Industrial Engineering
Faculty of Applied Science & Engineering | University of Toronto
Tel: 647-654-6977 Email: Samantha.hopkins@mail.utoronto.ca

You are being asked to take part in a MASc research study from Human Factor and Applied Statistic Lab at the University of Toronto. Before agreeing to participate in this study, it is important that you read and understand the following explanation of the proposed study procedures. The following information describes the purpose, procedures, benefits, discomforts, risks and precautions associated with this study. In order to decide whether you wish to participate or withdraw in this research study, you should understand its risks and benefits to be able to make an informed decision. This is known as the informed consent process. Please ask the investigator to explain any words you don't understand before signing this consent form. Make sure all your questions have been answered to your satisfaction before signing this document.

Purpose

This study aims to understand driver's behavior under specific conditions. As a participant you will be asked to:

1. Fill out a series of questionnaires
2. Wear measurement devices on your body
3. Drive through a simulated environment

Procedure

There are 6 parts to this study:

1. Screening and Recruitment: You were asked to fill out a screening questionnaire to provide information on your driving history and habits. Based on this information, your eligibility was assessed, and you were invited to take part in this research study.
2. Orientation and Training: You will be provided with written and verbal information on the experiment and its procedures. You will then be trained using the driving simulator, as well as on how to use an automated vehicle. This part will take about 25 min.
3. Equipment Calibration: A head-mounted eye tracking system (measuring glance location), heart rate sensors, and two video cameras are used in this experiment. These systems will be calibrated. The heart rate electrodes will be placed on your chest in 3 locations (one at the top and bottom of your sternum, and one on the bottom left side of your rib cage). One video camera will be trained

on your feet to see how you use the pedals, and the other video camera will be trained on the driving environment. This part will take about 15min.

4. Experimental Drives: You will complete 7 drives in the simulator (3 driving sessions), each about 10 minutes long. Before and after each experimental drive, you will complete questionnaires. You will also be given a 5-minute break between each experimental session. This portion will take about 90 minutes.
5. Post-experiment Questionnaire: At the end of the experiment, you will be asked to complete a post-experiment questionnaire, which will take 15 to 20 minutes.
6. Compensation: You will be compensated with cash and will sign a receipt of your compensation.

Risks

There are no major risks involved in this experiment as the tasks are not physiologically demanding or psychologically stressing. However, we want to make you aware of two possible issues:

1. The possibility of simulator sickness (a form of motion sickness specific to simulators). Especially upon first using a driving simulator, there is a small chance of feeling dizzy, nauseous, or fatigued. If you feel any of these symptoms appear, please immediately stop the experiment and inform the investigator. The investigator will also monitor for any signs of simulator sickness. The possibility of becoming motion sick during this experiment is about 1 in 40 participants.
2. You may experience discomfort when wearing the electrodes for heart rate. The electrodes have an approximate 1" radius, and are attached to the skin through an adhesive surface. Adhesives are safe for skin contact, and adhesive residue is removable by wiping it with a paper towel, or washing it with soap and water if necessary. You will be provided with a paper towel and wet wipes to clean your skin. Disposable adhesive pads will be used during the experiment.

Benefits

There are several benefits to conducting this study. The most important benefit is your contribution to research in traffic safety. You will also gain experience with academic research and be able to use and test out a state of the art driving simulator.

Compensation

The experiment is expected to last for approximately three hours. At the end, you will receive payment at the rate of $14/hr, plus up to $8 in bonus for good performance. Good performance is correctly interacting with you assigned secondary task, while also driving safely. Hence, the maximum total compensation is $50 ($14/hr x 3hr + $8 bonus).

You may withdraw from the study at any time. If a withdrawal should occur, you will be compensated on a pro-rated basis at $14 per hour for your involvement to that point. Compensation will be pro-rated to the next half-hour increment. You will not receive a performance bonus if you choose to withdraw before the experiment is completed.

Confidentiality

All information obtained during the study will be held in strict confidence. You will be identified with a study number only, and this study number will only be identifiable by the investigators. No names or identifying information will be used in any publication or presentation. No information identifying you will be transferred outside our research facilities.

Please be advised that we video-record the experimental trials with five cameras. Three will capture the pedals, one will capture the steering wheel, and another will capture the overall scene (including the steering wheel, the dashboard and the secondary task display). We will use an eye-tracking device to track and record where you are looking during the experiment. The videos will only be seen by the primary investigator, as well as co-investigators and faculty supervisor's research assistants and research collaborators. Your face will not be in any video.

The research study you are participating in may be reviewed for quality assurance to make sure that the required laws and guidelines are followed. If chosen, (a) representative(s) of the Human Research Ethics Program (HREP) may access study-related data and/or consent materials as part of the review. All information accessed by the HREP will be upheld to the same level of confidentiality that has been stated by the research team.

Participation

Your participation is voluntary, and you may refuse to participate, may withdraw at any time during the experiment, and may decline to answer any question or participate in any parts of the procedures/tasks – all without negative consequences. If you choose to withdraw at any point during the experiment, your data will be deleted within one month. Only your name will be kept on record, unless you request otherwise. Should you decide to withdraw subsequent to your completion of the experiment, you may only do so up until the point that the primary investigator has commenced preliminary analysis.

Additional Information

As electrodes will be placed on your body, it is recommended to wear clothes that you can easily place an electrode under, such as looser, or button down shirts. It is also recommended to not wear a dress, because placement of the electrodes will be more difficult. When you come in, you will be shown a drawing of how to place the electrodes (one on the top of your sternum, one on the bottom of your sternum, and one on the bottom left side of your rib cage). If you don't feel comfortable placing the electrodes correctly yourself, a person of the gender of your choosing will be able to assist you.

Additionally, if you choose to participate in this study, please do not wear any eye makeup, as that will interfere with our eye tracking hardware.

Location

The experiment will be conducted in the Human Factors and Applied Statistics Lab, located at the Rosebrugh Building (RS), 164 College Street, Toronto, ON M5S 3G8.

Questions

You can contact the Office of Research Ethics at ethics.review@utoronto.ca, or 416-946-3273, if you have questions about your rights as a participant. If you have any general questions about this study, please call 647-XXX-XXXX or email samantha.hopkins@mail.utoronto.ca

Consent

I have had the opportunity to discuss this study and my questions have been answered to my satisfaction. I consent to take part in the study with the understanding I may withdraw at any time. I have received a signed copy of this consent form. I voluntarily consent to participate in this study

______________________	______________________	______________________
Participant's Name (please print)	Signature	Date

I confirm that I have explained the nature and purpose of the study to the participant named above. I have answered all questions.

______________________	______________________	______________________
Investigator's Name	Signature	Date

Appendix G: Pre-Experiment Questionnaire

Pre-experiment Questionnaire

Basic Information:

(Filled in by experimenters)

Participant ID: ____

Date: _____

Modified Complacency-Potential Factors (Singh et al., 1993)

Please fill out the questionnaire below.

1. I think that automated devices used in medicine, such as CT scans and ultrasound, provide very reliable medical diagnosis.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
2. Automated devices in medicine save time and money in the diagnosis and treatment of disease
   Strongly Disagree 1---2---3---4---5 Strongly Agree
3. If I need to have a tumor in my body removed, I would choose to undergo computer-aided surgery using laser technology because it is more reliable and safer than manual surgery.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
4. Automated systems used in modern aircraft, such as the automatic landing system, have made air journeys safer.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
5. ATMs provide a safeguard against the inappropriate use of an individual's bank account by dishonest people.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
6. Automated devices used in aviation and banking have made work easier for both employees and customers.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
7. Even though the cruise control in my car is set at a speed below the speed limit, I worry when I pass a police radar speed trap in case the automatic control is not working properly.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
8. I would rather purchase an item using a computer than have to deal with a sales representative on the phone because my order is more likely to be correct using the computer.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
9. Bank transactions have become safer with the introduction of computer technology for the transfer of funds.
   Strongly Disagree 1---2---3---4---5 Strongly Agree
10. I feel safer depositing my money at an ATM than with a human teller.
   Strongly Disagree 1---2---3---4---5 Strongly Agree

At the end of this page, please stop, and hand the tablet back to your experimenter.

Trust

Modified Checklist for Trust between People and Automation (Jian, Bisantz, & Drury, 2000a)

Below is a list of statements for evaluating trust between people and automation. There are several scales for you to rate intensity of your feeling of trust, or your impression of the system **based on the experimenters explanation, and demonstration of the vehicle's automation.** Please mark an "x" on each line at the point which best describes your feeling or your impression.

(Note: not at all=1; extremely=7)

1) I am confident in the system

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

2) The system provides security

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

3) The system is dependable

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

4) The system is reliable

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

5) I can trust the system

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

6) I understand the system

1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

Appendix H: Within Experiment Questionnaire

Basic Information

Filled by experimenters
1) Participant ID

____

2) Date

____

3) Scenario No: __

NASA-TLX

Part 1. Scaling

The purpose of this questionnaire is to assess your subjective workload for the scenario you just completed. While providing your ratings, please consider both the driving and the non-driving tasks that you just performed.

If you need clarification on a question, please do not hesitate to ask the experimenters. Thank you for your time!

The definition of the subscales used in this questionnaire are as follows. They will appear again while you are doing the following questionnaire.
· **Mental Demand** - How much mental or perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching etc.?) Was the task easy or demanding, simple or complex?
· **Physical Demand -** How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating etc.?)
· **Temporal Demand** - How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
· **Own Performance -** How stressful do you think you were in accomplishing the goals of the task? How satisfied were you with your performance in accomplishing these goals?
· **Effort -** How hard did you have to work (mentally and physically) to accomplish your level of performance?
· **Frustration Level** - How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Please keep these definitions in mind while you assign the rates and weights in the following questions.

1) Mental Demand - How much mental or perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching etc.?) Was the task easy or demanding, simple or complex?
Question: How mentally demanding was the task?

Very Low Very High*
1 _________________________[__]______________________________ 20

2) Physical Demand - How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating etc.?)
Question: How physically demanding was the task?

Very Low *Very High* *
1 _________________________[__]______________________________ 20

3) Temporal Demand - How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Question: How hurried or rushed was the pace of the task?

Very Low *Very High**
1 _________________________[__]______________________________ 20

4) Performance - How stressful do you think you were in accomplishing the goals of the task? How satisfied were you with your performance in accomplishing these goals?
Question: How successfully were you in accomplishing what you were asked to do?
(BE CAREFUL, THE BAR IS FROM Perfect to FAILURE from LEFT to END for this question)

Perfect *Failure**
1 _________________________[__]______________________________ 20

5) Effort - How hard did you have to work (mentally and physically) to accomplish your level of performance?
Question: How hard did you have to work to accomplish your level of performance?

Very Low *Very High**
1 _________________________[__]______________________________ 20

6) Frustration Level - How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?
Question: How insecure, discouraged, irritated, stressed and annoyed were you?

Very Low *Very High**
1 _________________________[__]______________________________ 20

Part2: Pair Comparison

Now please examine the following pairs of the subscales. For each pair, highlight the element that you feel contributed more to your workload in the last scenario that you completed.

7) ( ) Mental Demand ( ) Physical Demand

8) ( ) Mental Demand ( ) Temporal Demand

9) ( ) Mental Demand ( ) Performance

10) ( ) Mental Demand ( ) Effort

11) ( ) Mental Demand ( ) Frustration

12) ( ) Physical Demand ( ) Temporal Demand

13) ( ) Physical Demand ( ) Performance

14) ( ) Physical Demand ( ) Effort

15) ( ) Physical Demand ( ) Frustration

16) ( ) Temporal Demand ( ) Performance

17) ( ) Temporal Demand ( ) Effort

18) ( ) Temporal Demand ( ) Frustration

19) ( ) Performance ( ) Effort

20) ( ) Performance ( ) Frustration

21) ( ) Effort ( ) Frustration

Risk Perception Questionnaire

The scenario you just drove was As Risky As:

( ) 10: driving with my eyes closed; A crash is bound to occur every time I do this

( ) 9: passing a school bus that has its red lights flashing and the stop arm in full view

( ) 8: driving just under the legal alcohol limit with observed weaving in the lane

( ) 7: in between 6 & 8

( ) 6: driving 20 miles per hour faster than traffic on an expressway

( ) 5: in between 4 & 6

( ) 4: driving 10 miles an hour faster than traffic on an expressway

( ) 3: in between 2 & 4

( ) 2: driving on an average road under average conditions

( ) 1: driving on an easy road with no traffic, pedestrians, or animals while perfectly alert

Situation Awareness Rating Technique (SART)

Situation Awareness is defined as "timely knowledge of what is happening as you drive."

Situation Awareness Rating Technique (SART)	
DEMAND	
Instability of Situation	Likeliness of situation to change suddenly
Variability of Situation	Number of variables which require your attention
Complexity of Situation	Degree of complication (number of closely connected parts) of the situation
SUPPLY	
Arousal	Degree to which you are ready for activity
Spare Mental Capacity	Amount of mental ability available to apply to new tasks
Concentration	Degree to which your thoughts are brought to bear on the situation
Division of Attention	Amount of division of your attention in the situation
UNDERSTANDING	
Information Quantity	Amount of knowledge received and understood
Information Quality	Degree of goodness or value of knowledge communicated
Familiarity	Degree of acquaintance with the situation

Please rate the level of each component of situation awareness you perceived in the last scenario that you completed.

DEMAND

Instability of situation: Low 1---------2---------3---------4---------5---------6---------7 High

Variability of situation: Low 1---------2---------3---------4---------5---------6---------7 High

Complexity of situation: Low 1---------2---------3---------4---------5---------6---------7 High

---

SUPPLY

Arousal: Low 1---------2---------3---------4---------5---------6---------7 High

Spare mental capacity: Low 1---------2---------3---------4---------5---------6---------7 High

Concentration: Low 1---------2---------3---------4---------5---------6---------7 High

Division of attention: Low 1---------2---------3---------4---------5---------6---------7 High

---

UNDERSTANDING

Information quantity: Low 1---------2---------3---------4---------5---------6---------7 High

Information quality: Low 1---------2---------3---------4---------5---------6---------7 High

Familiarity: Low 1---------2---------3---------4---------5---------6---------7 High

Trust

Modified Checklist for Trust between People and Automation (Jian et al., 2000a)

Please fill out the questionnaire below for the automated vehicle system you experienced in the last scenario (i.e., combined adaptive cruise control and lane keeping assistance).

Please mark an "x" on each line at the point which best describes your feeling or your impression.

(Note: not at all=1; extremely=7)

1) I am confident in the system

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

2) The system provides security

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

3) The system is dependable

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

4) The system is reliable

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

5) I can trust the system

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

6) I understand the system

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

7) I feel comfortable engaging in a secondary task when the automation is on

   1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7

Acceptance

Please fill out the questionnaire below for the automated vehicle system you experienced in the last scenario (i.e., combined adaptive cruise control and lane keeping assistance).

I find the system:

Please mark an "x" on each line at the point which best describes your feeling or your impression.

I find such a system / the (...) system (please tick a box on every line)

	Strongly	Somewhat	Neutral	Somewhat	Strongly	
1. Useful	◯	◯	◯	◯	◯	Useless
2. Pleasant	◯	◯	◯	◯	◯	Unpleasant
3. Bad	◯	◯	◯	◯	◯	Good
4. Nice	◯	◯	◯	◯	◯	Annoying
5. Effective	◯	◯	◯	◯	◯	Superfluous
6. Irritating	◯	◯	◯	◯	◯	Likeable
7. Assisting	◯	◯	◯	◯	◯	Worthless
8. Undesirable	◯	◯	◯	◯	◯	Desirable
9. Raising Alertness	◯	◯	◯	◯	◯	Sleep-Inducing

Appendix I: Post-Experiment Questionnaire

1) Participant ID

____

2) Date

____

3) Group Number

____

Questionnaire on Display Type

Please respond to the following statements for each of the experimental conditions.

(Logic based on group number: if group 1, then will show questions specific to the Take-over request display. If group 2, then will show questions specific to the reliability display.)

<u>Group 1:</u>
I liked the following experimental condition.

- No display
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Take-Over Request
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental condition helped me understand what was going on with the automation.

- No display
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Take-Over Request
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental condition made me feel safer while driving.

- No display
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Take-Over Request
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental conditions helped me anticipate failures before they occurred.

- No display
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Take-Over Request
    - (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The take-over request improved my monitoring technique of the **road** environment as compared to no display.

- o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I monitored the **road** environment more when there was no display than when there was a take-over request.

- o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

<u>Group 2:</u>

I liked the following experimental condition.

- No display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Reliability Display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental condition helped me understand what was going on with the automation.

- No display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Reliability Display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental condition made me feel safer while driving.

- No display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Reliability Display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The following experimental conditions helped me anticipate failures before they occurred.

- No display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)
- Reliability Display
  - o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The reliability display improved my monitoring technique of the **road** environment as compared to no display.

- o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I monitored the **road** environment more when there was no display than when there was a reliability display.

- o (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

Questionnaire on Failure Types

(Logic based on group number: if group 1, then will show questions specific to the Take-over request display. If group 2, then will show questions specific to the reliability display.)

As you may have noticed, there were two different types of failures that occurred in the scenario, 1) failures that occurred at intersections and 2) failures that did not occur at intersections, i.e. seemingly random.

Please respond to the following statements.

I noticed the above breakdown in failure types.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated the failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated the failures at the intersections.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated potential failures whenever I saw buildings off the road.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated potential failures whenever I noticed a change in the road scenery.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated the non-intersection**/random** failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

The limitations of the system were clearly relayed to me at the beginning of the experiment.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I only truly understood the limitations of the system once I started driving the automated car in the experiment.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I only truly understood the limitations of the system once I drove the automated car in the no display condition, and experienced the failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 1) The take-over request experimental condition helped me anticipate the non-intersection failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 2) The reliability display experimental condition helped me anticipated the non-intersection.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated the non-intersection**/random** failures during the no-display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 1) The take-over request experimental condition helped me anticipate the intersection failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 2) The reliability display experimental condition helped me anticipate the intersection failures.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I anticipated the intersection failures during the no display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 1) I started to anticipate the intersection failures after the take-over request experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 2) I started to anticipate the intersection failures after the reliability display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I started to anticipate the intersection failures after the no display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 1) I started to anticipate the non-intersection**/random** failures after the take-over request experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

(Logic: Group 2) I started to anticipate the non-intersection**/random** failures after the reliability display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

I started to anticipate the non-intersection**/random** failures after the no display experimental condition.

- (Strongly Disagree) 1 --- 2 --- 3 --- 4 --- 5 --- 6 --- 7 (Strongly Agree)

Driving History

1. On a scale of 1 to 10, with 1 being very unsafe and 10 being very safe, how safe a driver do you think you are?

1	2	3	4	5	6	7	8	9	10
Very Unsafe							Very Safe		

14. In the past three years, how many times have you been stopped by a police officer and received a **warning** (but no citation or ticket) for a moving violation (i.e. speeding, running a red light, running a stop sign, failing to yield, reckless driving, etc.)?

Enter a number (enter 0 for none.): ___________

15. In the past three years, how many times have you been stopped by a police officer and received a **citation or ticket** for a moving violation?

Enter a number (enter 0 for none.): ___________

16. In the past three years, how many times have you been in a **vehicle crash** where you were the driver of one of the vehicles involved?

Enter a number (enter 0 for none.): ___________

Driving Style Questionnaire

1. To what extent these driving behaviors apply to you?

Not at all   Neutral   Very much

a. Fuel-conserving:
b. Aggressive:
c. Relaxed:
d. Lawful:
e. Conservative:
f. Distracted:
g. Time-conscious:
h. Tense:
i. Attentive:
j. Calm:
k. Environmentally-conscious:
l. Sporty:
m. Safe:
n. Risky:
o. Predictive/Anticipatory:
p. Courteous:
q. Passive:
r. Fluid/Smooth:
s. Intentional:
t. Reactionary:
u. Deliberate:

2. How often do you…

<u>Never</u>, <u>Rarely</u>, <u>Occasionally/ Sometimes</u>, <u>Often</u>, <u>Very Often</u>

1) find yourself having looked away from the road for longer than you intended to?
2) find yourself being surprised by what you see on the road, after having looked away from the road?
3) looked away from the road and are surprised by how slow/fast you are going when you glanced back at the speedometer?
4) find yourself drifted out of your lane because you looked away from the road?
5) turn off your cellphone/tablet before driving to reduce distractions while driving?

Manchester Driver Behavior Questionnaire

Nobody is perfect. Even the best drivers make mistakes, do foolish things, or bend the rules at some time or another. For each item below you are asked to indicate HOW OFTEN, if at all, this kind of thing has happened to you. Base your judgments on what you remember of your driving. Please indicate your judgments by circling ONE of the options next to each item. Remember we do not expect exact answers, merely your best guess; so please do not spend too much time on any one item.

1. How often do you do each of the following?
   Never, Hardly ever, Occasionally, Quite Often, Frequently, Nearly all the time

a. Try to pass another car that is signaling a left turn.
b. Select a wrong turn lane when approaching an intersection.
c. Failed to “stop” or “yield” at a sign, almost hit a car that has the right of way.
d. Misread signs and miss your exit.
e. Fail to notice pedestrians crossing when turning onto a side street.
f. Drive very close to a car in front of you as a signal that they should go faster or get out of the way.
g. Forget where you parked your car in a parking lot.
h. When preparing to turn from a side road onto a main road, you pay too much attention to the traffic on the main road so that you nearly hit the car in front of you.
i. When you back up, you hit something that you did not observe before but was there.
j. Pass through an intersection even though you know that the traffic light has turned yellow and may go red.
k. When making a turn, you almost hit a cyclist or pedestrian who has come up on your right side.
l. Ignore speed limits late at night or very early in the morning.
m. Forget that your lights are on high beam until another driver flashes his headlights at you.
n. Fail to check your rear-view mirror before pulling out and changing lanes.
o. Have a strong dislike of a particular type of driver, and indicate your dislike by any means that you can.
p. Become impatient with a slow driver in the left lane and pass on the right.
q. Underestimate the speed of an oncoming vehicle when passing.
r. Switch on one thing, for example, the headlights, when you meant to switch on something else, for example, the windshield wipers.
s. Brake too quickly on a slippery road, or turn your steering wheel in the wrong direction while skidding.
t. You intend to drive to destination A, but you ‘wake up’ to find yourself on the road to destination B, perhaps because B is your more usual destination.
u. Drive even though you realize that your blood alcohol may be over the legal limit.
v. Get involved in spontaneous, or spur-of-the moment, races with other drivers.
w. Realize that you cannot clearly remember the road you were just driving on.
x. You get angry at the behavior of another driver and you chase that driver so that you can give him/her a piece of your mind.

Susceptibility to Driver Distraction Questionnaire (SDDQ)

Please answer the following questions using:

Never; Rarely; Sometimes; Often; Very Often

1. When driving, I …

a. Have phone conversations.

b. Manually interact with a phone (e.g., sending text messages).

c. Adjust the settings of in-vehicle technology (e.g., radio channel or song selection).

d. Read roadside advertisements.

e. Continually check roadside accident scenes if there are any.

f. Chat with passengers if you have them.

g. Daydream.

Please answer the following questions using:

Strongly Disagree; Disagree; Neutral; Agree; Strongly Agree

2. I think it is alright for me to drive and…

a. Have phone conversations.

b. Manually interact with a phone (e.g., sending text messages).

c. Adjust the settings of in-vehicle technology (e.g., radio channel or song selection).

d. Read roadside advertisements.

e. Continually check roadside accident scenes.

f. Chat with passengers.

3. I believe I can drive well even I…

a. Have phone conversations.

b. Manually interact with a phone (e.g., sending text messages).

c. Adjust the settings of in-vehicle technology (e.g., radio channel or song selection).

d. Read roadside advertisements.

e. Continuously check roadside accident scenes.

f. Chat with passengers.

4. Most drivers around me drive and…

a. Have phone conversations.

b. Manually interact with phones.

c. Adjust the settings of in-vehicle technology (e.g., radio channel or song selection).

d. Read roadside advertisements.

e. Continuously check roadside accident scenes.
f. Chat with passengers if there are any.

5. Most people who are important to me think, it is alright for me to drive and...

a. Have phone conversations.
b. Manually interact with phones.
c. Adjust the settings of in-vehicle technology (e.g., radio channel or song selection).
d. Read roadside advertisements.
e. Continuously check roadside accident scenes.
f. Chat with passengers.

Please answer the following questions using:
Never; Rarely; Sometimes; Often; Very Often; Never Happens

6. While driving, I find it distracting when...

a. My phone is ringing.
b. I receive an alert from my phone (e.g., incoming text message).
c. I am listening to music.
d. I am listening to talk radio.
e. There are roadside advertisements.
f. There are roadside accident scenes.
g. A passenger speaks to me.
h. Daydreaming.

Demographics

The following are standard questions that allow researchers to determine how representative the group of participants in a study is of the general population. Remember, filling out this questionnaire is voluntary. Skipping any question that makes you feel uncomfortable will not exclude you from the study.

1. Please describe the highest level of formal education you have completed:

   a. Some high school or less
   b. High school graduate
   c. Some college
   d. College graduate
   e. Some graduate education
   f. Completed graduate or professional degree (e.g. Masters, LCSW, JD, Ph.D., MD, etc.)

2. Are you: (Please circle all that apply.)

   a. A full time student
   b. A part time student
   c. Unemployed
   d. Retired
   e. Employed full time
   f. Employed part time
   g. A full time caregiver (e.g. children or elder)
   h. A part time caregiver (e.g. children or elder)
   i. None of the above

5. Please provide the city and province where you drive most often:

   City:________________________

   Province:_____________________

Appendix J: Analysis for understanding the different types of failures

Linear mixed models, combined with a priori contrasts, were used for variable analysis. For the following dependent measures, variance stabilizing transform were not identified, and therefore, an unstructured variance/covariance matrix was used to create their linear models:

- Hands-On-Wheel Time (s)
- Reaction Time – ALF Off (s)
- Standard Deviation of Steering Wheel Angle (degrees)
- Maximum Acceleration (m/s^2)
- Angular Acceleration (degrees/s)
- Max Angle

No transform was required for the following dependent measures:

- Angle Range

The linear model consists of 3 independent variables: Display Type, Display Present and Failure Number. Display Type can be either the TOR or the reliability display, meaning that the participant is in the group that experiences the TOR, or in the group that experiences the reliability display. Display Present can be either Yes or No, meaning that there is either no display, which is a baseline drive, or that a display is present. And Failure Number can be either P1, P2, U1 or U2. Each of these values indicates a different failure that the participant experienced. P1 indicates the first predictable failure in a scenario, while P2 indicates the second predictable failure in a scenario. U1 indicates the first unpredictable failure in a scenario, while U2 indicates the second unpredictable failure in a scenario. Given each of these options, there are 16 possible takeover situations for all participants. These takeover situations are depicted in the graph in Figure 27, and they are labeled 1-16. Each point in the graph represents the value of a dependent variable for the given scenario. Each model used Table 42for guidance to create the necessary contrasts to understand the failure types.

In order to examine the impact of the different failure types, only the no display failure situations were used for creating the contrasts.

The contrasts were set up as follows:

A) Difference between the first and second predictable failures (P1 vs P2):

$$\frac{(1+9)-(2+10)}{2}$$

B) Difference between the first predictable failure and the first unpredictable failure (P1 vs U1):

$$\frac{(1+9)-(5+13)}{2}$$

C) Difference between the first predictable failure and the second unpredictable failure (P1 vs U2):

$$\frac{(1+9)-(6+14)}{2}$$

D) Difference between the second predictable failure and the first unpredictable failure (P2 vs U1):

$$\frac{(2+10)-(5+13)}{2}$$

E) Difference between the second predictable failure and the second unpredictable failure (P2 vs U2):

$$\frac{(2+10)-(6+14)}{2}$$

F) Difference between the first and second unpredictable failures (U1 vs U2):

$$\frac{(5+13)-(6+14)}{2}$$

Table 42: This table displays and labels each of the different failure scenarios that are used for the contrasts

TOR								Reliability							
No Display		Display Present		No Display		Display Present		No Display		Display Present		No Display		Display Present	
P1	P2	P1	P2	U1	U2	U1	U2	P1	P2	P1	P2	U1	U2	U1	U2
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16

Appendix K: Effect of Participant Failed on Takeover Quality

The binary variable for Time Out of Lane is called "Participant Failed", which is equal to 1 if the participant left the lane, and 0 if the participant stayed in the lane. This analysis only looks at unpredictable failure scenarios, and uses both unpredictable failures that occur in the scenario. The variable Participant Failed was added to the linear models used to assess the takeover quality variables. This new linear models were created with the SAS MIXED procedure, and used display type, display present, failure type and Participant Failed as fixed factors and participant as a random factor. As the homogeneity of variance assumption was not met, an unstructured variance covariance matrix was chosen.

As expected, Table 43 shows that when a participant fails, and leaves the lane by any amount, the quality of their takeover is significantly poorer. On average, the Maximum Acceleration After Take-Over increases by .5 m/s^2, the angle range increases by 3.5 degrees, the maximum angle increases by 2.7 degrees, the standard deviation of steering increases by .7 degrees, and the standard deviation of lane deviation increases by .1m. When the driver leaves the lane, they need to compensate for leaving the lane, and therefore have to oversteer to return to the center of the lane. Subsequently, it appears that participants need to steer more as they familiarize themselves with manual driving, and their environment, which could indicate a greater workload. This is indicated by the Standard deviation of steering and the standard deviation of lane deviation.

Table 43: The interactions of the takeover quality variables with the binary variable, Participant Failed, which measures whether or not a participant left the lane

	Estimate	t-Value	p-Value
Maximum Acceleration After Take-Over (m/s^2)	0.49	t(34)=3.76	0.0006
Angle Range (degrees)	3.45	t(34)=2.65	0.012
Maximum Angle (degrees)	2.67	t(34)=2.99	0.005
Standard deviation of steering (degrees)	0.74	t(34)=3.65	0.0009
Standard Deviation of Lane Deviation (m)	0.12	t(34)=5.37	<.0001