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Improving Drivers' Behaviour When Partial Driving Automation Fails

Yalda Ebadi
University of Massachusetts Amherst

IMPROVING DRIVERS' BEHAVIOUR WHEN PARTIAL DRIVING AUTOMATION FAILS

A Dissertation Presented

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YALDA EBADI

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YALDA EBADI

Approved as to style and content by:

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Shannon C. Roberts, Chair

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Donald L. Fisher, Member

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Michael Knodler, Jr., Member

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Sundar Krishnamurty, Department Head

Mechanical & Industrial Engineering

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ABSTRACT

IMPROVING DRIVERS' BEHAVIOUR WHEN PARTIAL DRIVING AUTOMATION FAILS

SEPTEMBER 2020

YALDA EBADI

B.S., ISLAMIC AZAD UNIVERSTY OF TEHRAN

M.S., UNIVERSITY OF TEHRAN

Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Dr. Shannon C. Roberts

With the advent of automated vehicle systems, the role of drivers has changed to a more supervisory role. However, it is known that all vehicles with Level 2 (L2) systems have a very specific operational design domain (ODD) and can only function on limited conditions. Hence, it is important for drivers to perceive the situations properly and regain the control from the L2 system when needed. As suggested by past research, designing an informative interface could help drivers in their new supervision and intervention role while driving with L2 vehicles by providing feedback to drivers when hazards or event that may cause system failure are detected. On the other hand there are many situations where these vehicles cannot detect hazards and provide any feedback prior to the event. In these cases, training programs which provide drivers with an experience of these system limitations and allow them to practice dealing with such limitations can prove to be effective countermeasures. The objective of the current study is to employ different methods (designing HMI and training drivers) to increase drivers' situational awareness regarding operational design domain (ODD) and improve drivers performance in transfer of control situations while driving with level 2 (L2) automation features. This study includes two experiments- in first experiment, an informative dashboard interface was designed and tested through three phases (observation, prototyping, testing). Results from the testing phase showed that drivers who received the newly designed dashboards took back control more effectively and had more situational awareness compared to the control group. In the second experiment, a PC-based training program was designed and tested to improve drivers takeover response and situational awareness when L2 systems reach their ODD limits. Results showed drivers in the PC-based training group took back control more effectively when L2 systems reached their ODD limits and had more situational awareness compared to the drivers who received user manual or placebo training.

EXECUTIVE SUMMARY

This research has been conducted through two experimental studies. In the first experiment, new Human-Machine Interface (HMI) was designed and tested for dashboard of Level 2 (L2) vehicles. In second experiment drivers situational awareness and performance will be improved further by training. In both experiments we focus on L2 systems (drivers support features (DSF)) that have Adaptive Cruise Control (ACC) and Lane Centering Assistant System (LCAS).

The first experiment included three phases. In the first phase an observational study was conducted on a driving simulator followed by an interview. In this phase a simple dashboard design (Original dashboard design) was presented to the drivers while driving in L2 simulated scenarios. The objective of this phase is to determine if drivers over-rely on automation in scenarios where transfer-of-control is critical to road user safety and, if so, what interface might better support transfer-of-control. Through interviewing we identified the interface requirement of drivers based on their responses and utilized this knowledge for the second phase.

In the second phase , two dashboard interfaces (Basic Dashboard, Advanced Dashboard) were then prepared through four design iterations (Prototype, Co-design sessions, heuristic evaluation and pilot testing). In third phase, the effect of new dashboard designs on participants' performance and satisfaction was investigated though another driving simulation study. Forty two participants were randomly assigned to three group based on the dashboard design (Advanced, Basic, Original). They drove through seven scenarios which were designed to represent several situations where L2 systems reached their operational design domain (ODD) limit and required participants to take back control from the system. The results from this phase showed that, displaying information regarding road geometry increased the number of successful take back control for participants in Advanced Dashboard group compared to Basic and Original Dashboard groups. To further investigate take back control action of participants, takeover time to hazard for each group was analyzed. The results showed that participants in the Advanced Dashboard group took back control sooner (6.4 seconds) than participants in Basic Dashboard (4.1 seconds) and Original Dashboard groups (1.5 seconds). Results also indicated that the participants in the Advanced Dashboard group were more situationally aware than the participants in the Basic Dashboard group and those in the Basic Dashboard group were more situationally aware than those in Original Dashboard groups while driving in L2 mode.

While the result from first experiment showed that drivers situational awareness and performance can be improved by providing feedback through an efficient HMI design, there are many situations where an L2 system cannot detect hazards on the road and provide feedback through an HMI. Moreover, at complex situations which present latent hazards, an L2 system cannot predict such situations and it is vital for participants to have prior knowledge about the system capabilities and limitations to take back control and mitigate the potential hazards. Plus none of the commercially available L2 vehicles have an HMI interface similar to Advanced Dashboard designed in first experiment. This raises the need for alternative methods to improve drivers performance and take back control quality in current L2 vehicles which can be used by users of these systems. Looking at results from third phase of first experiment, it is evident that participants who drove through scenario using basic dashboard were less situationally aware and took back control significantly later than those that used Advanced Dashboard design. Considering that Basic Dashboard design is similar to the dashboard designs found in current L2 models, it might be helpful to explore other available options to improve drivers' performance while using L2 dashboards. Hence in second experiment of this study, a training program for drivers will be designed to improve drivers knowledge of ODD limitation for those situations which are not detected by the system and also improve their take back control performance for those situations where system can provide them with take back control request (Similar to Basic Dashboard Design).

In second experiment a training program was designed to improve ODD situation awareness when a DSF reaches the limits of its ODD and help drivers to take back control more efficiently. Similar to past training programs, an active method for error training (Ivancic IV & Hesketh, 2000), known as the 3M approach (Fisher et al, 2017; Romoser & Fisher, 2009; Zafian et al., 2016) was used. More specifically, drivers were exposed to scenarios in which they made mistakes related to safety. Next, they received feedback and an explanation of how to mitigate their mistake. Finally, drivers were given an opportunity to master the skill. The training was delivered through a PC-based training program.

Next, the training program was evaluated to determine if it improves ODD situation awareness and take back control quality when a L2 system reaches the limits of its ODD. To allow for a controlled environment to evaluate driver behavior, this phase will employ the high-fidelity driving simulator housed in the UMass Human Performance Laboratory (HPL). The between-subjects independent variable in the experiment is the training program (either control (i.e., placebo training), user manual or the PC-based training program). The within-subjects independent variable in the experiment was the scenario. The post-test drives were used to assess the effectiveness of the training program. Results showed that drivers in the PC-based training program took back control more successfully and had more situational awareness when compared to the drivers in user manual and placebo training groups.

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CHAPTER 1

INTRODUCTION

1.1. Problem Statement

Driver support features (DSF) have changed the role of the driver from an active operator to a passive supervisor (Louw et al, 2017). However these features have a very specific operational design domain (ODD) (SAE International, 2018) and only function at limited roadway types, within finite geographic areas, within certain speed ranges, and under precise environmental conditions (National Highway Traffic Safety Administration, 2018). For example, some of these vehicles may have more sensitivity to road design (e.g., may not work on sharp curves, merge), may not recognize lane markings in poor visibility (Cadillac, 2018; Tesla, 2019). Hence, when the automated system reaches the limit of its ODD, drivers may experience unexpected behavior. For example, for one manufacturer, Adaptive Cruise Control (ACC) does not detect a vehicle ahead if it is not completely inside the driving lane (Cadillac, 2018). Hence, considering all the limitations of DSF, it necessary for the driver to perceive the hazardous situation, regain control of the vehicle, and maneuver through the hazardous situation (Greenlee et al, 2019).

Past research has shown that drivers either misperceive or oversimplify partial automation features' capabilities (McDonald et al , 2017) and they only remember the limitations if they experience them (Beggiato et al , 2015). At the same time, past research has shown that when drivers know what to in unexpected situations, they can respond within seconds (Duncan et al, 1991). There are several methods suggested to help drivers with their new supervisory role using support features. Designing an effective interface has been suggested as one of the method to help drivers with their supervision and intervention role while driving with DSF (Van den Beukel et al, 2016). However, designing an interface cannot address all the issues regarding the drivers lack of knowledge about DSF limitations. In complex situations where DSF does not detect or predict hazards, it is vital for participants to have prior knowledge about the system capabilities and limitations. As such, training programs that provide drivers with an experience of the system limitations and allow them to practice dealing with such limitations can prove effective as countermeasures to unexpected behavior of the systems due to reaching their ODD limitations (Beggiato & Krems, 2013).

1.2. Overarching Dissertation Objective

The objective of this proposed research is to design and test methods to improve drivers' responses when L2 systems reaches its ODD limitations. Within the framework of this overarching goal, two research objectives has been developed.

Objective 1:

The objective of first experiment is to develop and test an in-vehicle interface for use in DSF contexts, with a focus on delivering feedback and alerts when drivers need to make a manual transition between L2 (combination of Adaptive Cruise Control and Lane Centering System) and manual (L0). The study has been conducted in three experimental phases according to the human-centered design process, wherein users and designers are jointly responsible for system development (François et al, 2017). The first phase focuses on iterative development and in-vehicle interface design through an observational study conducted on a driving simulator followed by an interview. Results from the first phase were used to conceptualize and design a prototype interface for the second phase. In the second phase, another group of participants were provided with prototypes in a co-design session. Results from this experiment were aggregated to prepare a second prototype and apply it to the simulator cab's dashboard. This was followed by a heuristic evaluation, carried out by four human factors specialists, to improve the design. Prior to the third phase, a pilot session was conducted to finalize the design. In the third phase, 42 participants were recruited to test the effectiveness of the newly designed interface. Each phase and its corresponding hypothesis will be explained in the following sections.

Objective 2 :

The objective of second experiment is to develop and test a training program for use in DSF contexts, with a focus on training drivers to gain experience of the system limitations and allow them to practice dealing with such limitations. This training particularly aimed to improve drivers situational awareness and take back control quality while using DSF. To design the training, a 3M approach (Fisher et al, 2017; Romoser & Fisher, 2009; Zafian et al., 2016) was used. In this approach drivers were exposed to scenarios in which they would make mistakes related to safety. Next, they received feedback and an explanation of how they could mitigate their mistake. Finally, drivers were given an opportunity to master the skill. The training was delivered through a PC-based training program. The effectiveness of the training was then evaluated using pre/post test driving session on simulator.

1.3. Dissertation Organization

This dissertation focuses upon two experimental study. Chapter 2, provides a background on previous work that is relevant to the two projects. Chapters 3 and 4 each contain one of the two projects. Within each chapter the specific motivation for that project is discussed, followed by the methods, results of the study, discussion of significant findings and limitations, and a conclusion. Chapter 5 contains the overall conclusions from this dissertation work along with possible areas of future work relating to each project.

CHAPTER 2

BACKGROUND

In the following chapter, I will first give an introduction about Driver Support Features and Automated Driving Features. This will be followed by human factors challenges of using Driver Support Features including limited knowledge of drivers, disengagement of Drivers, situational awareness and transfer of control. After which a subsection regarding the countermeasures for addressing the aforementioned challenges has been included. This chapter will be concluded with a summary of all the sections as well as the objective and the hypotheses of the study.

2.1. Driver Support Features and Automated Driving Features

Bel Geddes in his 1940 book 'Magic Motorways' envisioned developments in the highway design and transportation and predicted several revolutionary ideas in the field of transportation. One of his ideas was to remove human from the driving process (Gedes, 2013). This revolution in transportation predicted almost 75 years ago is fast becoming a reality with major developments in automated vehicle technology. Perhaps the advent of automated vehicles in the 21st century will modernize transportation similar to how airplanes and motor cars did in the 20th century.

Automated vehicles have progressed rapidly in the past decade. Industrial giants such as Google, Tesla, General Motors etc. have all heavily invested in both systems in the past few years. These systems have the potential to cause a major shift in terms of how drivers interact with their vehicles (Milakis et al, 2017). Automated vehicle technology is expected to contribute towards improving roadway safety (Anderson et al., 2014). This important since it has been reported that when considering the last event in the crash causal chain, drivers were assigned as the critical reason for 94% of the crashes (Singh, 2015). Automated vehicles can be programmed to obey traffic rules (such as maintaining speed limits), have faster reaction times than human drivers and be informed about upcoming roadway conditions (Fagnant & Kockelman, 2014; Flämig, 2015).

Another advantage of this technology could be reducing the stress of the driver with regards to the driving task within the vehicle, by reducing their driving duties within the vehicle (Anderson et al., 2014). In addition to this, they are also expected to be environmentally friendly by improving fuel efficiency and cutting down greenhouse emissions (Guerra, 2016; Howard & Dai, 2014). These benefits will be extended by offering older residents, children, and persons with disabilities (especially for those living in areas which lack public or alternative means of transport) with a reliable mode of travel which the system navigate independently without any human drivers. (Anderson et al., 2014). In general, automated vehicle technology has a potential to improve productivity and society and this is expected to expand as the technology rapidly develops (Coles, 2016).

The SAE International introduced six-level classification system for automation in 2014, ranging from fully manual (Level 0) to fully automated systems (Level 5), where the driver needs to perform all driving tasks at Level 0 and at Level 5, the system has full vehicle control. Levels 0 through 2 requires the human to monitor the driving environment and are typically referred to as Drivers Support Features. Level 1 (driver assistance) and level 2 (partial automation) features are capable of performing only part of the dynamic driving task (DDT), and thus require a driver to perform the remainder of the DDT, as well as to supervise the feature's performance while engaged. As such, these features, when engaged, support, but do not replace, a driver in performing the DDT. Level 3 through 5 are referred to as Automated Driving Features (ADF) where the automated driving system monitors the driving environment (SAE International, 2018). Table 1 shows the detailed definitions for all the levels of driving automation.

Table 1. Level of Driving Automation, Definitions and Roles of human drivers

Level	Name	Definition	Longitudinal and lateral control	Monitoring driving environment	DDT fallback	System Operational design domain
0	No Automation	The driver performs all of the DDT	Driver	Driver	Driver	N/A
1	Driver assistance	A driver assistance system of either steering or acceleration/decelerat ion is present The diver perform the remaining task not performed by driving automation system.	Driver and System	Driver	Driver	Limited
2	Partial Driving Automation	One or more driver assistance systems of both steering and acceleration/decelerat ion are present The diver perform the remaining task not performed by driving automation system.	System	Driver	Driver	Limited
3	Conditional Driving Automation	Automated driving system perform all the aspects of DDT. Drivers will still need to intervene when takeover request is issued by the system	System	System	Driver	Limited

4	High Driving Automation	Automated driving system perform all the aspects of DDT. even if the driver fails to respond adequately to takeover request by the system	System	System	system	Limited
5	Full Driving Automation	The system performs all of the DDT in all conditions manageable by a human driver	System	System	system	Unlimited

2.2. Level 2: Human Factors Concerns

Both theoretical and empirical literature suggests that the introduction automated vehicle features to perform traditional driving tasks handled by a human driver will alter their role, thereby introducing several safety-critical human factors issues (Strauch, 2018). These may include problems regarding changes in the physical and mental workload (Young & Stanton, 2002), deskilling (Stanton & Marsden, 1996; Trösterer et al., 2016), vigilance decrement (Greenlee et al, 2018), takeover issues (Li et al, 2019), mode confusion (Endsley & Kiris, 1995), and reduced situation awareness (Parasuraman & Riley, 1997b).

As mentioned, in L2 systems, two of the primary driving functions are performed by the system, but the driver holds responsibility for monitoring the driving and should be ready to intervene and take back control from the system at all instances during the driving task. There are several concerns with drivers operating automated cars, and all are related to over-reliance on the automation and a subsequent failure to take over control (Buckley et al, 2018; Parasuraman & Riley, 1997). First, and perhaps most important challenge of these vehicles is regarding the drivers' lack of knowledge about the systems. The drivers may get confused about system functions and limitations (Gibson et al., 2016). Second is related to driver disengagement from some of the driving tasks which depends of the drivers level of trust on automation (McGuirl & Sarter, 2006). Third, it is challenging for drivers to maintain their vigilance as often as when they are driving manually (Merat & Lee, 2012) and consequently, their situational awareness may be decreased leading to failure to detect uncommon, complex situations that they otherwise would normally detect (Jones, 2015). However, activating vehicle automation means that drivers need to be responsible for maintaining situational awareness at all times.

Considering the above challenges, in this research work, we classified the human factors concerns regarding L2 systems into four main categories, namely, the lack of knowledge regarding the system, driver disengagement, lack of situational awareness, and challenges regarding transfer of control while using the system. The following sections will discuss these categories in detail.

2.2.1. Limited Knowledge of Drivers

In manual cars with no support features, the drivers learning process was fast since the basic controls of the vehicle could be mastered easily with minimal need to understand complex mechanism of the vehicles. The arrival of automated features in vehicle raises new challenges for drivers to understand these complex systems as well as adapt to the rapid developments in the field. With this in mind, knowledge of drivers or rather lack of knowledge, about the automation functions of the vehicles becomes a major concern.

It is suggested that drivers' understanding of the system features and their ability to adapt their behavior and skills to these systems have a direct effect on the actual effectiveness of the driver support features (DSF) (Sullivan et al, 2015). Despite this, previous studies showed that drivers had poor awareness regarding the automated systems in their vehicles. McDonald et al (2018) in a survey study reported that 20% of all drivers did not know if certain functions were available or not in their vehicles (McDonald et al, 2018).

The varying nomenclatures of similar automated features by different manufacturer may raise additional challenges for drivers to understand or recall the functionalities of these features. Funkhouser et al (2017) suggested that assigning similar sounding names to features with different functionalities may also create confusion even for those drivers who declared that they understood the system well (Funkhouser et al, 2017).

In L2 vehicles drivers need to be aware of system limitation and intervene when needed. One major challenge addressed in literature is that the drivers may get confused regarding whether they need to intervene or whether the system has the primary responsibility of driving (Gibson et al., 2016). Previous studies showed that drivers usually do not have sufficient knowledge of driving supported features. In part, this is because drivers frequently do not understand the ODD of L2 features and assume that the automation will function in a much broader domain than the one for which it was intended (Larsson, 2012a). To better understand this matter, we will need to define Operational Design Domain (ODD) and then explain the two important and prominent driving support features as well as their ODD limitations. The first feature is regarding longitudinal control of the vehicle (Adaptive Cruise Control (ACC)) and second, is regarding lateral control of the vehicle (Lane Centering feature).

2.2.1.1. Operational Design Domain

SAE (2018) defines an Operational Design Domain (ODD) as "operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics". The ODD of a system is a representation of conditions within which the specific driving automation feature operates, and each of these features has exactly one ODD (SAE International, 2018).

According to NHTSA (2017), vehicle manufacturer are encouraged to prepare documentation specifying information regarding the ODD for each of the DSF available on their vehicles. The documented ODD should be able to inform the users about specific conditions where the feature is intended to function. A typical ODD documentation should provide information regarding DSF limitations such as speed range, road types, geographic area, environmental conditions and etc. (NHTSA, 2017).

Koopman & Fratrik (2019) stated that ODD should be characterized by at least one of the following factors (Koopman & Fratrik, 2019) :

1) Operational terrain along with location-dependent parameters (e.g. curvature, road friction, banking, etc.)
2) Environmental and weather conditions (e.g. wind, visibility, icing, lighting, etc.)
3) Operational infrastructure and availability of navigation aids (e.g. beacons, lane markings, traffic lights, signage, etc.)
4) Rules of engagement and on-road policies (e.g. traffic laws, social norms, customary signaling, etc.)

5) Considerations for implementation in multiple regions/countries (e.g. side-of-road changes, stop sign modifiers, etc.)
6) Communication modes, bandwidth, latency, stability, availability, reliability, including both machine-to-machine communications and human interaction.
7) Availability of continuous updated data regarding infrastructures or road-way conditions (e.g. construction zones, traffic jams, etc.)

Considering all the above factors, ODD concept in vehicle automation context was introduced to define the limitations of automation systems at levels 1, 2, 3 and 4, while Level 5 (full driving automation) has an unlimited ODD (SAE International, 2018). Czarnecki (2018) categorized ODD limitation in to three groups - road environment, vehicle performance, and vehicle state (Czarnecki, 2018).

Limitations regarding road-environment include types of roads (urban, rural, freeways), particular roadway structures such as tunnels or roundabouts, and weather and visibility conditions. Czarnecki (2018) also stated that the road-environment limitations are the most common elements of an ODD. In addition to this, ODD limitations regarding vehicle performance and state are also important. Vehicle performance (behavior) limitations may include speed or maneuverability limitations and vehicle state limitations may include the constraint such as loading limitations, vehicle modifications, etc.

In the following section, the ODD limitations for L2 vehicles will be explained by providing an insight on the ODD limitations for longitudinal and lateral support features in L2 vehicles.

2.2.1.2. Operational Design Domain: Longitudinal Control

The Operation Design Domain of a driving support feature defines “where (such as the type of roads or speed limits) and when (under what conditions, such as day/night, weather limits, etc.), the feature has been designed to operate safely” (NHTSA, 2017). Ideally, if the system falls outside its defined ODD or dynamically changes to fall outside its ODD, the vehicle should transition to conditions that pose minimal safety risks (NHTSA, 2017). We will first explore the ODD and ODD limitations for the longitudinal control feature of the vehicle.

Adaptive Cruise Control is one of the most common DSF in modern vehicles, which provides assistance towards the vehicle’s longitudinal control, thereby reducing the workload of the driver in the vehicle (ISO, 2018). A typical Adaptive Cruise Control allows the driver to set a desired speed and safe headway distance from the lead vehicle by using buttons on the steering wheel or lever switches in the vehicle. The system maintains the vehicle’s speed setting imposed by the driver, in the absence of a lead vehicle. In the case where a lead vehicle is present in vehicle’s path, a safe headway distance, either set by default or by the driver is applied, in turn adjusting the vehicle’s speed to the lead vehicle’s speed (Bianchi et al. 2014).

The current DSF have several design limitations, such as sensor limitations or malfunction or failure in sensor processing which could affect the features’ performance (Beggiato & Krems, 2013; Bianchi Piccinini et al, 2014). They also may not be able to deal with critical traffic situation on their own, requiring the driver to remain in the active driving role, with the features only providing assistance to the driving task (Nilsson, 1996). By exploring the vehicle owner’s manuals of different DSF, it is possible to observe the numerous situations where the ACC system reaches its ODD limitations, such as, in presence of pedestrians and/or stationary objects, or when the system is not able to detect the lead vehicle appropriately at different roadway geometries and conditions. For example, the vehicle owner's manual of Cadillac SuperCruise states "On curves, ACC may not detect a vehicle ahead in your lane. You could be startled if the vehicle accelerates up to the set speed, especially when following a vehicle exiting or entering exit ramps. You could lose control of the vehicle or crash. Do not use ACC while driving on an entrance or exit ramp"(Cadillac, 2018). In another example, from the vehicle owner's manual of Tesla Model X states that its adaptive cruise control feature "…cannot detect all objects and may not brake/decelerate for stationary vehicles or objects, especially in situations when you are driving over 50 mph (80 km/h)" (Tesla, 2019).

Despite the documented limitations of ACC from various sources, many users of the system do not have the accurate or complete knowledge or understanding of the system and its limitations. For example, a survey study showed that among the 370 users of the ACC system, about 72% of the users did not have sufficient knowledge of ACC functionality and limitations (Jenness et al, 2008). In a similar study, 60% of the drivers reported to read only the half of the user's manual while the rest of the drivers did not read it at all (Mehlenbacher et al, 2002). In Another study, drivers with no previous experience with ACC showed a lack of proper mental model regarding the system and this was worse in case of those drivers who did not read the manual (Larsson, 2012).

2.2.1.3. Operational Design Domain: Lateral Control

A Lane Centering Assist System (LCAS) is another DSF available in modern vehicles, which controls the lateral positioning of the vehicle by continuously steering the vehicle to keep it centered within a lane. The combination of an LCAS and an ACC system is equivalent to a Level 2 Automated Vehicle (Ismail, 2017). The literary sources on LCAS is often conflicting, with some theoretical works suggest that a driver can disengage from physically operating the steering wheel, by taking their hands off the steering wheel from time to time (Ismail, 2017), while in practice, manufacturer sources such as the owner's manual of the Tesla X suggest that drivers need to keep their hands on the steering wheel at all times when using the LCAS feature (Auto Steer) of the vehicle (Tesla, 2019). However, there is common ground for all sources about LCAS, which state that the driver is required to be mentally present behind the wheel at all times while using these features.

There are several ODD limitations regarding LCAS, mentioned in owner's manuals of different vehicle models. Some of the common limitations include the inability of the LCAS to function properly in poor visibility of the lane markings due to weather conditions (heavy rain, snow, fog etc.), or roadway conditions (damage or obstructions caused by mud, ice; damaged bumpers). The system could also fail to function appropriately at certain road geometries such as narrow or winding roads (Cadillac, 2018; Tesla, 2019). Despite all these limitation, unlike ACC there is a significant lack of literature about the drivers' knowledge of lateral control systems.

Considering above mentioned operational design domain for both lateral and longitudinal control systems, lack of knowledge about these systems' capabilities and limitations may cause drivers' confusion regarding effectively using and interacting with the system. However, lack of knowledge is not the only human factors challenge faced while driving L2 vehicles. Drivers may have enough knowledge about L2 systems capabilities and limitations but they may still be affected negatively by using the systems due to the disengagement from driving control task (both lateral and longitudinal control). In the next section the challenge regarding drivers' disengagement while driving L2 vehicles and its consequences will be discussed.

2.2.2. Disengagement of Drivers

2.2.2.1. What is it?

Despite the mentioned benefits of automated systems on safety and comfort, research has shown that these systems may also negatively affect the drivers' abilities, behavior, and performance (Carsten & Nilsson, 2001; Saffarian, de Winter, & Happee, 2012). For instance, different studies have shown that such systems may decrease the driver demands and increases the chances of distraction (Reyes & Lee, 2004). This issue is more challenging for Level 1 and Level 2 automated systems, where drivers need to continuously cooperate with the system, sufficiently supervise the systems functions, and take back control when needed (Solis Marco, 2018).

Drivers support features help drivers maintain their vehicle's controls longitudinally, laterally, or both, allowing them to allot more processing resources to other tasks while driving (Blanco et al., 2015). These features alter the role of the driver from an active operator to a passive supervisor (Louw et al, 2017). During this transfer of role, drivers may experience the 'out-of-the-loop' phenomenon where they are not in control loop, which in case of L2 systems is the control of steering and speed maintenance of the vehicle (Navarro et al, 2016). There are three aspects of the 'out-of-the-loop' phenomenon: manual, cognitive, and visual. All manual, cognitive and visual aspects of driving are important and contributing to safe driving performance while using L2 vehicles. For example, keeping hands on the steering wheel at all times gives the drivers the physical control which provides feedback of steering torque and helps correct heading errors (Pick & Cole, 2006). Similarly, proper situation awareness and on-road monitoring is vital for decision-making and anticipating potential hazards, to effectively respond to critical events (Endsley, 2006).

As a result of driving with automated features engaged, drivers are removed from the manual control loop, since they are no longer physically operating the vehicle's controls like the steering wheel, throttle, and brake pedals (Stanton & Young, 1998). Similarly, drivers can also be removed partially or completely from the cognitive control loop. In these cases, being 'out-of-the-loop' can also result in mental underload, due to the reduced involvement of the driver in continuous control tasks (M. S. Young & Stanton, 2002), thereby leading to decrease in situation awareness, drowsiness, and inattention (Greenlee et al, 2018; Hirose et al, 2015). Drivers can also be removed from the control loop by visual distractions which impairs their ability to estimate the situation on the road and decide to intervene if needed (Zeeb et al, 2016).

One factor which can play an important role in drivers disengagement (out-of-the-loop) in automated vehicle is their trust in the automated features of the vehicle. In the following sections we will explore all the aspects related to drivers disengagement while driving L2 vehicles- the trust in automation, and different types of driver distraction.

2.2.2.2. Trust and over-reliance

Various definitions of trust have been used in the context of automation. Mayer et al (1995) characterized trust as an intention, stating that trust is "…the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that party" (Mayer et al, 1995). In their definition of trust, Lee and See (2004) viewed it as an attitude, stating that trust is "…the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (J. D. Lee & See, 2004).

Understanding or possessing the right knowledge of the automated system has been shown to be the strongest factors influencing trust (Balfe et al, 2018). One of the ways to present the information to drivers is through an in-vehicle interface which presents appropriate amount of information regarding the system's functions which could increase operator's trust (Hoff & Bashir, 2015), by enabling them to understand or predict the system's actions (Endsley, 2017). An efficient interface with sufficient availability of information (Bitan & Meyer, 2007) and accurate and adequate feedback (Muir & Moray, 1996; Sharples et al., 2007), could lead to the development of trust in a driver.

In addition to knowledge and understanding two other factors - driver's experience and level of automation could impact driver's trust on automation systems. Previous studies showed that drivers' experience could play an important role in the development of trust as drivers' trust in the system evolves with more experience using the system (Cohen et al, 1998; Wickens & Hollands, 2000). This is evident when considering the reliance of the drivers with varied experience. Novice drivers (drivers with less expertise) tend to rely inappropriately on the systems compared to experienced drivers (Fan et al., 2008; Sanchez et al, 2014). Another factor is the level of automation (0-5) which may influence the level of drivers' trust towards automation system (French et al, 2018). Previous studies have shown that at higher level of automation drivers trust the system less due to system being more complex for the drivers to understand than at lower levels (Lewis et al, 2018; Merritt et al, 2015).

It is suggested that the efficiency of automated systems often depends on the drivers' level of trust in those systems (Payre et al, 2016) and to maximize the efficiency, an appropriate calibration of trust is needed. An appropriate calibration of trust is said to occur when the drivers' level of trust matches the capabilities of the system. Poor calibration could result due to over-trust and distrust. Over-trust occurs when the person's trust in the automated system is too high when compared to the supposed capabilities of the system. This in turn causes over-reliance on the system which may result in misuse of the system, i.e. driver expects the automation to perform tasks outside its capabilities or even when the system is malfunctioning.

On the other hand, distrust refers to a person not having sufficient degree of trust (J. D. Lee & See, 2004). This may result to under-reliance which may lead to disuse of the system, i.e. lack of usage of the system despite its capabilities, resulting in increased physical and mental workload for the drivers and inefficient system performance (Lee & Moray, 1992). Considering the above, appropriate calibration of trust is vital for safe and optimum performance and drivers with an appropriate calibration of trust, can effectively complete tasks even with an imperfect automation system. Appropriate calibration of trust can result in faster braking responses (Seppelt & Lee, 2007) and also drivers confidence while using the system (Dzindolet et al, 2003). Previous study showed that providing information regarding system's capabilities and limitations can help drivers to calibrate their trust on automated systems appropriately. (Khastgir et al, 2018)

Drivers' overreliance and misuse of automation has been addressed as an issue in previous studies. At unexpected events, drivers who reported higher level of trust in the automation system were shown to have slower reaction times while using the system (Payre et al, 2016). Previously, different studies have also indicated that the inappropriate calibration of trust can lead to similar negative effects at different levels of automation (Abe et al, 2002; McGuirl & Sarter, 2006; Parasuraman & Riley, 1997). One of the reasons for this could be the drivers visual scanning activity, where drivers with high trust in the system tend to monitor less (Bagheri & Jamieson, 2004). Results from Korber et al (2018) showed that participants with higher level of trust spent less time looking at the road while performing a distraction task (Körber et al, 2018). This shows that perhaps those drivers who have more trust on automation are more prone to be distracted while driving with these systems. In the following section we will discuss more about the effect of automation system on drivers' distraction and inattention.

2.2.2.3. Distraction: Types

One of the attractive aspects of driving support features for consumers is that it reduces drivers' involvement in the control task and enables them to be engaged in non-driving tasks. In fact, various studies showed that the presence of support features in vehicles can cause changes in drivers' behavior in many aspects including the increased likelihood of drivers engagement in non-driving distractive tasks (Brookhuis, De Waard, & Janssen, 2019; O. Carsten, Lai, Barnard, Jamson, & Merat, 2012; Merat, Jamson, Lai, & Carsten, 2012a). In other word, support features will increase the likelihood of drivers to redirect their attention from the active driving task to passive supervision and engagement in non-driving tasks and this trend goes up with increase in the level of automation. This tendency varies for different type of drivers support features, where drivers are more prone to inattentiveness to the driving task when using lateral support features compared to longitudinal support (Carsten et al., 2012).

Corresponding with three types of 'out of control loop'- visual, cognitive, manual which were discussed earlier in section 2.2.2.1, there are three respective types of distraction (Visual, Cognitive, Manual) that can accrue while using L2 system which will be addressed in the following sections.

2.2.2.3.1. Visual distraction

Visual distraction occurs when the driver neglects or fails to look at the road ahead, and instead focuses his/her visual attention on another target for an extended period of time (Zeeb et al, 2015). This type of distraction is one of the addressed issues in previous literature about level 2 automated vehicles (Carsten et al., 2012). Carsten et al (2012) showed that the prevalence of visual distraction increased when using driving support features in L2 systems. This was mainly due to the fact that L2 systems shift most of the responsibility of the driving task to the system and the drivers are left relatively uninvolved in a passive supervision role, leading to driver disengagement. This may lead to the driver shifting their attention away from the operations of the vehicle and onto distracting activities, either in-vehicle or in their external environmental (Carsten et al., 2012).

Visual distraction has also been shown to deteriorate the takeover quality of drivers in L2 vehicles. A previous study showed when reading news or watching a video, drivers did not maintain the lateral position of the car properly after taking back control from the system and they deviated about 8-9 cm from the lane center (Zeeb et al., 2016). Another study using standardized visual Surrogate Reference Task to simulate visual distraction, showed that visual distraction task significantly impaired the takeover time and quality of driver in highway setting. Results from this study showed that when visually distracted drivers had higher collision rates than when they were cognitively distracted, especially when traffic density was high (Radlmayr et al, 2014).

It is important to note that visual inattention and failure to monitor the roadway adequately due to usage of L2 systems is not only caused by visual distraction tasks such as texting or dialing on the phone, but also can be caused by using L2 systems alone. Although some studies showed that the non-distracted drivers responded similarly to critical events when driving in both manual and L2 vehicles in contrast to distracted drivers who performed worse in L2 mode (Merat et al, 2012b), another study has shown that when using automated features without any distraction tasks imposed, drivers were less likely to sufficiently monitor the area of roads where the visual information required the take back control was present. They suggested that resuming manual control is not only challenging in terms of performing the take back control action but also could be difficult due to the change of driver's visual strategies linked to drivers' disengagement from the steering task (Navarro et al., 2016).

2.2.2.3.2. Manual distraction

Manual or physical distracted driving occurs when drivers took one or both hands off the steering wheel for a long duration in order to physically manipulate objects (K. Young & Regan, 2007). Several studies have examined the effect of manual distraction tasks on drivers performance while driving using L1 and L2 systems. Some of these studies investigated the prevalence of manual distraction while driving with automation support features. Carsten et al (2012) showed that drivers engagement in eating task increased while driving using L1 systems compared to manual driving and increased further while using L2 systems. The result from the same study showed that the mentioned effect was different for longitudinal and lateral support systems. The drivers who used longitudinal support system were less likely to be engaged in eating task compared to those who used lateral support systems. The results showed that 91% of the drivers were engaged in eating task while using lateral support features and 68% of the drivers were engaged in eating task while using longitudinal support (Carsten et al., 2012). In another study, Llaneras et al (2013) showed that drivers engagement in texting was 42% more while using L2 systems (ACC and Lane keeping system) comparing to L1 system (ACC). The same study reported a similar result for cellphone dialing task (Llaneras et al. 2013).

2.2.2.3.3. Cognitive distraction

There are several definitions for cognitive distraction. Young & Regan (2007) suggested that "cognitive distraction includes any thoughts that absorb the driver's attention to the point that they are no longer able to navigate through the road environment safely" (KYoung & Regan, 2007). Strayer et al (2011) stated that cognitive distraction occurs when drivers allot a part of their attentional resources to non-driving related secondary task (Strayer et al, 2011).

Previous studies showed that cognitive distraction effects drivers performance while driving with automated support features. Merat et al (2012) showed that drivers reaction toward critical events on road was poorer in automated mode when they were engaged in cognitive task compared to those driving manually while engaged in the same task. The drivers in automated group could not mitigate the critical hazard situation properly (change lane) while they were performing the cognitive task (Merat et al., 2012b). Another study showed that the adverse effect of cognitive distraction task on drivers take over reaction while driving L2 vehicles was similar to visually-demanded distraction tasks, despite the fact that drivers had their eyes on road all the time (Radlmayr et al., 2014). However the result of this study indicated that the drivers who were engaged in visually distraction tasks had a higher total number of collisions in the high density traffic situation.

To sum up, the negative effect of drivers' disengagement, either caused by drivers' over-reliance on the system or different types of distraction, is one of the challenges faced by drivers while using L2 systems and can impact their performance significantly as mentioned in the above section. Another human factors challenge of using L2 systems addressed in previous studies, is reduced situational awareness of the drivers while driving L2 vehicles. This challenge has a strong relation to the two aforementioned challenges and will be discussed in the following section.

2.2.3. Situational Awareness

Situational awareness is one of the important mentioned factors while driving with automation support features where on one hand drivers role is altered to a more supervisory (Merat et al., 2012b) and on the other hand drivers may still need to regain manual control from the system when system reaches its ODD limits (Sheridan, 2006). To better understand the term situational awareness in driving context, we need to first have a look on situational awareness definition in the literature.

Previous literature has defined situational awareness as "perception of environmental elements and events with respect to time or space, the comprehension of their meaning, and the projection of their future status" (Endsley, 1995). Situational awareness has been considered as one of the critical factors which contributes to the driver's decision making process for mitigating hazards as well as planning and maintaining their safety (Sirkin et al, 2017). Endsley & Garland (2000) stated that situational awareness involves perceiving information and cues, fully understanding the meaning and nature of the required tasks and projecting this knowledge and recall it in future situations (Endsley & Garland, 2000). Hence as Merat & Jameson (2009) mentioned , a proper situational awareness is constituted by awareness of the vehicle's position on the roadway in relation to other roadway elements as well as how it can be maneuvered to safely navigate the roadway while mitigating the potential hazards that may arise (Merat & Jamson, 2009).

Due to the supervisory role of the driver while using L2 systems, they are more likely to shift their attention from the driving task to other secondary distraction tasks resulting in less situational awareness (Merat et al., 2012b). As mentioned earlier, it is vital for the drivers to be situationally aware since they may need to regain manual control from the system if the system is unable to mitigate particular situations (Sheridan, 2006). It has been recommended that for L2 drivers need to be situationally aware at all times while they should be able to become situationally aware and control the vehicle after brief period of disengagement.(NHTSA, 2016).

Despite the importance of drivers being situationally aware in automated vehicles, previous studies have shown that drivers' situational awareness is likely to be reduced while driving with automated support features which do not require continuous involvement of the driver in driving tasks (Hirose et al, 2015). While the literature about drivers situational awareness is vast, there have been different measurements used to quantify the situational awareness of the drivers. Merat & Jemsaon (2009) computed drivers' response time to unexpected hazards as a measurement of drivers situational awareness and they showed that drivers' situation awareness was reduced in automated driving condition (Hirose et al, 2015; Merat & Jamson, 2009). Other studies suggested using drivers hazards perception (in terms of monitoring and detecting the hazards) as a measurement for situational awareness (Horswill & McKenna, 2004). Related to this, Green lee et al (2018) showed that drivers hazard detection declined significantly during a 40-minute automated driving. By 'hazards', we mean those situations that system cannot function well in, due to reaching its operational design domain (ODD) limitations.

Regardless of the different situational awareness measurement, the decrease in situational awareness can be problematic, either causing less hazard detection or late response to hazards. This issue can be more challenging for those L2 systems which do not provide any warning to the drivers (Stephen Ridella, 2017). These type of L2 systems would require the drivers to be situationally aware of their surroundings all the time to detect possible takeover situations and finally, take back control when the system has met its limitations (Jones, 2015). Transfer of the control in general is one of the drivers challenge while using L2 systems since the system cannot function in all the situations. Next section will discuss the challenges regarding transfer of control while using L2 systems.

2.2.4. Transfer of Control

One particular issue of concern while using L2 is transfer of control between the system and the driver. Transition in L2 is defined as the process where the primary control mechanism in the human-machine interaction system changes from one state to another state (Lu et al, 2016). Transfer of control can either be initiated by the driver or the system.

A system initiated transfer of control occurs when a take back control request is issued to the driver upon reaching system limitations where driver intervention is required. On the other hand a driver can also initiate transfer of control if they anticipate that the system is reaching its ODD limitations or to meet their maneuvering or navigation goals (Merat et al, 2014).

Transition is particularly challenging in the case of level 2 automation since the system is not able to function during all the situations encountered on the roadway (Norman, 1990). As for L2 systems (combination of ACC and lane keeping assistance) drivers are expected to be available for control all times and to be ready to maneuver the vehicle to safety since the system might not warn the driver beforehand (Singh, 2015). Automated systems at L2 are not designed to work as chauffeurs or self-drive the vehicle but only to serve as support systems to assist the driver in various vehicle control tasks. In lower automation level such as L2 systems drivers are still required to provide input frequently even though DSF such as ACC and LCAS take away portions of driving task from the driver (Seppelt & Victor, 2016). For instance at curves, drivers may need to provide additional steering torque even though LCAS is engaged. They may also be required to take back control from ACC in presence of vulnerable road users such as pedestrians, bicyclists (Cadillac, 2018; Tesla, 2019).

As McDonald et al (2019) stated that a safe take back control depends on two important factors, first the takeover time budget and the effectiveness of the action. Further it was stated that a crash could be avoided, if drivers anticipated the take back situation, decided on an action and executed it properly on time. (McDonald et al., 2019). Past research have investigated the effectiveness of a wide range of takeover time budgets and the most commonly used value for time budget was 7 seconds (Eriksson et al, 2017; Payre et al , 2016; Zeeb et al, 2015).

Despite the impotence of drivers take back control actions, prior research has indicated that the response to critical road events by drivers in highly automated cars was slower than their response in manual cars (Young & Stanton, 2007). Previous research also showed that the interface of Telsa model S itself was inadequate at providing drivers with the information they need to understand ahead of time that it will be necessary for them to reassume control. A thematic analysis of video data in an on-road study featuring drivers in a Level 2 vehicle showed that drivers did not receive appropriate support from the system to fulfill their monitoring duties in order to efficiently take back control from the DSF (Banks et al, 2018) . There may even be a case where humans and the system miscommunicate, resulting in false expectations from both sides. This can either be over-reliance by the human on the system capabilities or the misconception by the system about what the human has or has not noticed. Both cases can have disastrous consequences (Carsten & Martens, 2019)

One of the factors which plays an important role in drivers reaction in transfer of control situations is the density of the traffic . Results obtained from a study conducted by Gold et al (2016) showed that the presence of traffic at transfer of control situation was detrimental to the drivers takeover time and quality. They showed that at high traffic density drivers had longer take over times, had takeover reaction with less time budget, resulting in more crashes (Gold et al, 2016).

As mentioned in this section, there are several challenges in usage of L2 vehicles. One of the important issue is the drivers' lack of sufficient knowledge regarding L2 system capabilities and ODD limitations. False expectations and inappropriate calibration of trust can lead to over-reliance and misuse of the automation system (Parasuraman & Riley, 1997a). One negative consequence of over-reliance on system can be drivers' engagement in distraction tasks which decreases their situational awareness. As explained before, the situational awareness of drivers is less in L2 vehicles compared to manual vehicles. Being involved in secondary tasks may further decrease the vigilance of the drivers to the point that they cannot detect and mitigate the hazards on the road by taking back control from the L2 systems. Considering all the mentioned issues, it is vital to seek for practical solutions. In following sections, some of the most important suggested solutions addressed in previous literature will be explained.

2.3 Level 2: Countermeasures

Finding solutions to minimize the negative effects while using the positive capacity of these systems is an important subject suggested by many researchers in the field (Saffarian et al., 2012; Seppelt & Victor, 2016). Previous studies investigate different tools and methods to overcome the challenges of L2 system. For example, they investigated the effect of user owner manuals (Jenness et al., 2008), pre-purchase training (Mullen, 2017), designing an appropriate interface (van den Beukel et al, 2016), providing post drive feedback (Körber et al. 2018), drivers state monitoring (Gaspar et al, 2018) and ODD training (Forster et al, 2019). Based on the focused aspect of these solutions, we classified them into two main groups - Improving drivers' knowledge, improving drivers' supervision and transfer of control. Owners' manual, pre-purchased training, designing an interface, post drive feedback are included as solutions which target the drivers' knowledge and understanding of the system and hence will be included in the drivers knowledge category. Driver's state monitoring and ODD training both mainly focus on improving drivers supervising the road/system and take back control when needed and hence they will be included in drivers supervision and transfer of control categories.

2.3.1 Drivers Knowledge

Literature regarding countermeasures for drivers lack of knowledge and understanding of L2 systems can be classified into four categories: Owners' manual, pre-purchase training, Realtime feedback and post drive feedback. Using comprehensive user manual documents is one of the methods to improve drivers knowledge of the system. as NHTSA (2017) also encouraged vehicle manufacturer to prepare documentation specifying information regarding the ODD for each of the DSF available on their vehicles (NHTSA, 2017). Another method is providing an informative in-vehicle interface which provides real-time feedback to the drivers can be another solution. Training drivers prior their usage of the system or after they have gained experience by using L2 systems is another suggested countermeasure. As we explained earlier, there are various situations where drivers need to be informed (HMI interface) or learn from (Training) about ODD limitations of the systems in order to decide correctly when to take back control from the system. In the following sections we discuss different countermeasure methods to help drivers to gain sufficient knowledge and awareness about ODD limitation of L2 vehicles while using them.

2.3.1.1 Owner's Manuals

Nowadays, most of the products include documentation from their manufacturer in form of owner's manual to provide essential information to the users. Basically these manuals aim to increase users' safety by explaining terms of use and providing hazard warnings. In case of automobiles, they can be extensive and complex due to the fact that they include all the information regarding getting started guides, troubleshooting guides, tutorials and so on (Mehlenbacher et al, 2002).

Introduction of new generations of vehicles with DSF or ADF has increased the complexity and extensiveness of these documents. As mentioned in earlier sections, there are many ODD limitations which L2 vehicle users need to be aware of in advance. There may be some cases where DSF may not function properly (e.g. snow or mud on the road resulting in sensors malfunctioning) and other cases where it will not function at all (e.g. L2 systems cannot detect vulnerable road users such as pedestrian, bicyclists) (Cadillac, 2018; Tesla, 2019). Hence, it is crucial for manufacturer to document and provide all the details and information regarding limitations of their L2 vehicles to the users and for the users to obtain this information and recall it while using these systems.

Considering L2 vehicles have been introduced recently to the consumer population (NHTSA, 2019), the most reliable and accessible source of information regarding these features is the vehicle owner's manual. A previous survey has reported that almost 70% of the respondent mentioned that they learned how to use ACC features using owner's manual (Jenness et al, 2008). In a more recent study conducted by Abraham et al (2016), participants were asked about their preferred method of learning about their vehicle technology and 63% of them indicated that they preferred vehicle owner's manual (Abraham et al., 2016).

The usefulness of owner's manuals is based on the manufacturers' assumption that all prospective users will read the entire manual and understand its contents specifically regarding systems' limitations. It has been found out that many people do not read the manuals completely, in fact Leonard and Kames (2000) reported that only 6.8 percent of

221 survey respondents indicated to have read their vehicle owner's manuals (Leonard & Karnes, 2000). Another issue is that although people might have read the entire manual they may not completely comprehend it as the survey results from Jenness et al (2008) also showed that despite 70% of the ACC users declaring that they read the manuals, only 28% were aware of the system functionalities and limitations (Jenness et al., 2008). This raises a question if there exists more effective methods to inform and educate the L2 vehicle users.

2.3.1.2 Pre-purchase/Pre-exposure Training

Owners' manual or trial and error are the most common learning method regarding safe use of automated vehicles (Eichelberger & McCartt, 2016; Jenness et al., 2008). However, owner's manuals have their own challenges as mentioned previously. Trial and error also may not be an effective method. Despite some studies showing that experience can help drivers become more aware of system limitations and adjust their driving behavior suitably, the complexity of the advanced vehicle technologies such as DSF may even render an experienced driver to face unexpected conditions while using these systems (Jenness et al., 2008; Larsson, 2012a). Previous studies also reported serious misconceptions of drivers prior to their purchase of automated vehicles resulting in them driving cars with false assumption about the functionality of their vehicles (Casner & Hutchins, 2019).

One solution can be providing drivers with pre-purchase training about automated features. A study conducted by State Farm insurance company showed that about 52% of the drivers preferred to be instructed about their new vehicle's functions at the dealership (Mullen, 2017). The quality of such pre-purchase training was evaluated for different dealership by Abraham et al (2017) and they found that the quality of training was not consistent across all dealerships. The study further reported that many salespeople who conducted the pre-purchased training failed to provide customers with adequate information about functionalities of automated features in the desired vehicles. Moreover, it was also suggested by many of these salespeople that training the drivers in a single session would not be effective and a follow-up training may be useful to make sure that drivers have gained the long-term knowledge about proper use of technologies in their vehicle (Abraham et al, 2017). Considering the above points it may be possible to improve the pre-purchase training by extensively training the salespeople, developing easy-to-understand material regarding automated features for consumers and also providing follow-up training opportunities to consumers.

Another form of user education regarding automated vehicles are interactive tutorials. These tutorials are being provided to the drivers in advance of their first interaction with an automated vehicle. They provide an opportunity for the drivers to make mistakes and learn from their errors. Besides, an interactive tutorial concentrates on specific set of tasks that users will face in real word comparing to the summarized information provided by owners' manuals. Another benefit of interactive tutorial relies on their capability to simulate a realistic depiction of the vehicle's HMI (Slater, 2003). Forster et al (2019) conducted a study investigating effectiveness of educating users prior to their exposure to the HMI of an automated vehicle using both owner's manual and interactive tutorial. Their results showed that interactive tutorial helped drivers to understand lane keeping system more accurately comparing the owner's manual. Similar results were also observed for drivers understanding of the ODD limitations where those who received interactive tutorial were more accurate in their description of the ODD of the system (Forster et al, 2019).

2.3.1.3 Real time feedback (HMI design)

To facilitate safe and smooth collaboration between drivers and driving automation systems, designing an effective Human-Machine interface (HMI) is essential, especially since no vehicle has reached level 5 automation. It is very likely that drivers of DSF equipped vehicles may not be aware that these systems cannot operate in all situations where the ODD limitations have been reached. A well-designed HMI will support drivers in their monitoring role and aid them in safely retrieving control (Hoc et al, 2009). Using sensors to detect the errors of the drivers and providing them with feedback in real-time, also has been considered by previous researchers (Panou et al, 2010).

There has been much focus on designing an effective HMI for L2 vehicles, which considers both driving with automation engaged and the transition where drivers take back control from the system (Rezvani et al., 2016). Three challenges have been identified in previous studies with regards to designing of an interface for L2 vehicles: (1) how to present information about system's status to avoid mode confusion (Kyriakidis et al., 2017); (2) how to deliver take-over requests to drivers (Banks et al, 2018); and (3) how to get drivers to place their attention back on-road (Blanco et al., 2015). Providing a feedback system may help in resolving these challenges. Visual, auditory, and tactile are three feedback types that can be incorporated separately or as combinations (Bengler et al, 2012).

The most basic visual feedback system in a L2 vehicle would show whether automation is engaged or not and it will only require a short glance from a driver to acquire such information (O. Carsten & Martens, 2019). A more advanced feedback system for L2 vehicles would include transfer-of-control information when vehicles reach their ODD limit. Some DSFs may have more sensitivity to complex road designs, may not recognize lane markings in poor visibility, or may be restricted in the amount of force needed to initiate an action (e.g., braking or steering). As such, when DSF reaches its ODD limitations, drivers may experience *unexpected* DSF behavior (Seppelt & Victor, 2016).

To sum up, an efficient design for an automation system is one that predicts its limitations and requests drivers to takeover control (O. Carsten & Martens, 2019). Previous studies have tested different interface designs to adequately support drivers during takeover. Van den Beukel et al. (2016) tested three in-vehicle interface designs that require drivers to take back control from the system. They recommended a combination of auditory, visual, and tactile feedback to support the driver while taking back control. Although van den Beukel et al. suggested an interface that assisted drivers in knowing *when* to take back control, their design did not provide any information about *why* drivers needed to take back control (van den Beukel et al, 2016). This is similar to real-world cases wherein actual DSFs, such as Cadillac Super Cruise, informs drivers to take back control, but does not provide any additional reasoning or information prior to the critical situation (Cadillac, 2018). This raises a question as to whether incorporating clues or additional information about critical situations would improve drivers' reaction time in takeover requests. Additionally, presenting appropriate clues and information prior to takeover requests may increase drivers situation awareness. This is important since situational awareness is likely reduced since DSF do not require continuous driver involvement (Hirose et al, 2015; Merat & Jamson, 2009).

Another question surrounds identification of information and cues presented in HMI that helps drivers take back control from L2 systems. Previous literature mentioned different situations where drivers need to be aware and take control from L2 systems. For example, drivers may need to put in additional steering torque at curves when using lane centering systems and need to take back control when lane markings are lost due to unexpected roadway conditions such as at merged sections (Seppelt & Victor, 2016). Another example is over-reliance on automation and passive road monitoring, which may lead to a failure to detect safety-critical zones such as pedestrian crosswalks at intersections (Gold et al, 2013). This can be dangerous since drivers might need to take back control due to the sudden appearance of pedestrians or a vehicle at intersections. Despite the importance of these situations, there is no literature about whether providing additional information along with takeover request through a HMI can assist drivers in taking back control.

2.3.1.4 Post drive feedback

Post-drive feedback is another approach to provide drivers with information and insight regarding functions and limitations of L2 systems. Some studies suggested that providing post-drive feedback regarding the reasoning of take-back control situations increases transparency of the system as well as drivers' understanding of the system (Körber et al, 2018). Previous study showed that an unexpected events (such as unexpected take back control situations) are stressful for drivers (Maule & Svenson, 2013) and providing an explanation after such events can decrease the negative effect, resulting in more feel of control (Koo et al., 2015).

Korber et al (2018) suggested that there are some challenges with prior and real-time feedback that post-drive feedback can address. Depending on the numerous situations where systems can reach their ODD limits and may need drivers intervention, it may not be possible to sufficiently provide an explanation beforehand. Moreover, providing explanation simultaneously with take back control request could possibly overload the processing capacity of the driver resulting in failure to take back control on time (Walch et al, 2015). Previous studies which compared the acceptance of real-time with post-drive feedback regarding drivers' performance showed that providing drivers with detailed information of their performance after driving was more acceptable than real-time feedback (Roberts et al, 2012). In context of automated driving, the results from Korber et al (2018) showed that proving an explanation for take back control request had no impact on trust but increase the drivers knowledge regarding systems' functions (Körber, Prasch, et al., 2018).

2.3.2 Drivers supervision and transfer of control

As Brookhuis et al (2008) stated, "Human beings notoriously get bad marks in (low frequency) vigilance tasks, that is, detecting occasional mishaps" (Kyriakidis et al., 2019). Introducing L2 vehicles changed the role of drivers to monitoring and supervising role. L2 vehicles enables the drivers to take their feet off the pedals and under specific conditions, even hands off the steering wheel for short periods. However, the drivers still need to be ready to take back control when needed. This presents a critical challenge for the drivers since using L2 systems can reduce drivers' subjective mental workload (Winter et al, 2014) and in extreme cases can cause cognitive underload which subsequently decreases drivers' situational awareness and vigilance (Young & Stanton, 2002) and slower their reaction when they need to take back control (Young & Stanton, 2007). A recent study by Marcos (2018) showed that cognitive underload effect can even occur after short period of time using L2 systems in the vehicles.

Considering the importance of maintaining constant attention and taking back control when needed, applying appropriate countermeasures may help drivers in their supervisory role and bypass the aforementioned cognitive underload negative effect. Drivers' state monitoring or training programs, are two suggested countermeasure methods to assist drivers in their supervisory role and also help them to take back control when needed (Marcos, 2018).

2.3.2.1 Drivers State monitoring

Drivers state monitoring (DSM) are systems that gather useful information about the drivers to evaluate their performance of driving task in context of safe driving practices (Waard et al, 1994) Modern technologies have given rise to new approaches to reduce drivers distraction and enhance drivers' safety. Camera-based systems have been used to track drivers head and eye movements towards the surroundings in order to detect inattention while driving. The information provided by such systems can be integrated in to HMIs to provide useful information and alerts to the drivers.

For instance, Fletcher et al (2007) came up with a new vision systems which monitored the drivers gaze as well as road way elements, capable of detecting lanes, pedestrians, signs and obstacles. It was suggested that when relevant information was missed by drivers, appropriate alerts could divert drivers attention towards the particular event on the road (Fletcher & Zelinsky, 2007).

The recent development of automated vehicles has changed the drivers' role (supervision) and making them more prone to distraction. The usage of DSM in this context could be helpful to understanding and adjusting according to drivers behavioral conditions (distraction, fatigue, drowsiness, etc.) while driving automated vehicles (Gonçalves & Bengler, 2015). Gaspar et al (2018) suggested that capabilities of DSMs could be used to provide alerts and keep the drivers within the control loop while driving automated vehicles. They showed that by providing alert reverting drivers attention back to the control loop, their situational awareness and take back control reaction was improved during unexpected automation failures. Their results indicated that not only DSM helped driver to be more situationally aware but also their take back control actions were improved using the system (Gaspar et al, 2018). An example of DSM can be seen in real word in Cadillac Super Cruise, where the drivers are monitored in real time using a camera-based system to provide alerts when they have been glancing off road for several seconds (Cadillac, 2018).

2.3.2.2 ODD Training

Improving drivers' knowledge and skills through training programs have been targeted in many different aspects. Previous works showed that skills related to visual search (Vlakveld, 2011), situation awareness (Walker et al, 2009), hazard anticipation (Pradhan, Fisher, & Pollatsek, 2005), hazard mitigation (Muttart et al, 2017) and attention maintenance (Pradhan et al., 2011) can be trained through specific training programs. Yamani et al (2016) showed that it is also possible to provide a shorter training integrating all three skills of anticipation, mitigation and attention maintenance (Yamani et al, 2016). Considering new generations of vehicles equipped with driver assistance features, new designed training programs are need to help drivers to improve their performance while interacting with such complex systems and this has been suggested as a possible solution by many researchers (Beggiato & Krems, 2013; Bianchi et al., 2014; Koustanaï et al, 2012; Larsson, 2012; Marcos, 2018). The issue of driving skill degradation while using automated vehicles was addressed in previous research and it was recommended to design and modify training programs to teach drivers about these systems capabilities and their responsibilities while interacting with such systems actions (Kyriakidis et al., 2019). However only few studies have been conducted regarding the effectiveness of training in this context.

Koustani et al (2012) showed that familiarization using simulator improved drivers performance while using forward collision warning (FCW) system. Their result showed that, driver performance measures such as time ahead, maximum deceleration, and response time, were improved significantly by simulator training compared to those drivers who received only users' manual as familiarization tool (Koustanaï et al., 2012).

Payre et al (2016) also conducted a study to investigate the effect of elaborated training on drivers performance while driving automated vehicles. In this study, they simulated a fully automated vehicle capable of handling all the overtaking, accelerating, braking and interacting with other vehicles . Two group of participants were assigned to simple and elaborated training groups where simple group had only a short familiarization and practice period on the simulator while the elaborated group were asked to read a text based information regarding the system functions and to answer questions. Results showed that the response time to emergency take back control situation was less for elaborated group compared to simple group. The elaborated group also showed more trust towards the system after interacting with the automated system on the simulator (Payre et al., 2016).

Forster et al (2019) conducted a study investigating effectiveness of educating automated vehicle drivers using interactive tutorial. Their results showed that interactive tutorial helped drivers to understand lane keeping system more accurately comparing the owner's manual. Similar results were also observed for drivers understanding of the ODD limitations where those who received interactive tutorial were more accurate in their description of the ODD of the system (Forster et al, 2019).

In another recent study, Noble et al (2019) showed that using an interactive training could help drivers to gain some knowledge regarding L2 systems. However their results showed that the training was not effective to improve drivers knowledge regarding the limitation of L2 systems. To investigate drivers knowledge regarding, they provided questionnaire to participants prior to the training, immediately after the training and after the driving with the vehicle. Their results showed that among 40 participants, only four after the training and two after the drives were able to identify all situations where ACC may not work as expected. For lane keeping, only one driver after the training and one after the drive responded to the questionnaires correctly. (Noble et al, 2019)

While all mentioned studies showed the effectiveness of training programs, there are few studies which showed that their training programs were not effective as they expected. Mueller et al (2019) showed that although training improves detection of Level 2 notifications for lane centering but this effect was not observed for adaptive cruise control (Mueller et al, 2019). Their results showed that their designed training program slightly improved drivers understanding of L2 system limitations.

2.4 Summarized Background

There has been rapid progress in the development of drivers support features in the past decade. The main goal of these vehicle systems is to assist drivers and improve roadway safety (Anderson et al., 2014). There are six levels of automation systems ranging from fully manual (Level 0) to fully automated systems (Level 5). In this classification, level 2 systems are those that are capable of performing some of the driving task and require a driver to perform the remainder of the tasks as well as to supervise the system. These systems have altered the role of the drivers, thereby introducing several safety-critical human factors issues (Strauch, 2018). The main issue of L2 vehicles have been associated with the need for drivers to be aware of system limitations and intervene when needed (Gibson et al., 2016). The human factors challenges regarding L2 systems can be classified into four main categories: the lack of knowledge regarding the system, driver disengagement while using the system, reduced situational awareness and challenging transfer of control. Drivers' understanding of the system features have a direct effect on the effectiveness of DSF (Sullivan et al, 2015). Previous studies have shown that drivers had poor knowledge regarding the vehicle automated systems (McDonald et al, 2018). Another challenge is regarding disengagement of the drivers. By controlling steering and speed maintenance of the vehicle, these systems also alter the role of the driver from an active operator to a passive supervisor (Louw et al, 2017) and thereby disengage the driver from the active control loop (Navarro et al, 2016). Trust on automation systems plays an important role on drivers disengagement. Appropriate calibration of trust is vital for safe performance and decrease the negative effect of driver disengagement phenomenon in automated vehicles (Seppelt & Lee, 2007).

Disengagement of drivers from the active control loop can effect drivers in different aspects. It increases the likelihood of driver distraction (Reyes & Lee, 2004) and reduces drivers situational awareness (Merat & Jamson, 2009). These systems enable drivers to be engaged in non-driving tasks resulting in distraction (Reyes & Lee, 2004) and this is more challenging for Level 2 automated systems, where drivers need to continuously cooperate with the system, sufficiently supervise the systems functions, and take back control when needed (Solis Marco, 2018). These systems also have shown to reduce drivers' situational awareness (Merat & Jamson, 2009) which is vital to perceive the oncoming situations and regain manual control from the system if needed (Sheridan, 2006).

The above-mentioned human factors concerns raises a need for practical solutions. It is crucial to provide drivers with comprehensive information about systems status, capabilities, limitations and to help them understand and predict the proper action (Körber et al., 2018). Owners' manual, pre-purchase training, real-time feedback through a proper HMI design , post drive feedback are different countermeasures to improve drivers knowledge regarding L2 systems as suggested in literature. Additionally there are countermeasures to help drivers in their supervision role as well as effective transfer of control: Drivers State monitoring and ODD Training.

Despite the important role of countermeasures such as real-time feedback through in-vehicle interfaces and drivers' training, there are only a few studies that have been done regarding these subjects in the context of L2 vehicles. As mentioned earlier in this chapter, designing an efficient interface which provides information about L2 systems limitations, can help drivers to better understand the system and perform safer while facing those situations where L2 systems reach their limits. Note that there are many situations where

L2 systems cannot provide feedback to the drivers, therefore for such situations we need to find another solution to help drivers to understand the systems' limitations in advance. Training is one suggested solution, hence, this dissertation specifically focuses on designing and testing effective methods (HMI design and training of the drivers) to improve drivers' performance while using L2 systems. In the last section of this chapter, the objective and research questions of this dissertation will be explained.

2.5. Objective and Research Questions

The objective of this proposed research is to design and test methods to improve drivers' behavior when L2 systems reaches its ODD limitations. Within the framework of this overarching goal, two research objectives has been developed and two separate experiment have been conducted. In this section, each research objective, questions and corresponded hypothesis will be discussed.

1) First experiment (objective, research questions): The objective of the first experiment is to design and test in-vehicle interfaces to improve drivers performance in transfer of control situations while driving with L2 systems. First experiment focused on designing in-vehicle interfaces which provide additional feedbacks when drivers need to take back control from L2 system. This experiment aimed to answer following research questions:

    - Can designing a new interface improve drivers' performance in transfer of control situations in L2 vehicles?
    - Can designing a new interface improve drivers' situational awareness in transfer of control situations in L2 vehicles?

- Can designing a new interface improve drivers' satisfaction while interacting with L2 systems?

2) Second experiment (objective and research questions): The objective of the second experiment is to develop and test a training program for use in DSF contexts, with a focus on training drivers to gain experience of the system limitations and allow them to practice dealing with such limitations. This experiment aimed to design a PC-based training program based on 3M approach (Mistake, Mentoring, Mastery) and test the effectiveness of the training program using post-test driving session on the simulator. The research questions of this experiment are as follows:

    - Can training result in more successful take back control attempts for those situations where L2 systems reach their ODD limitations?
    - Can training improve drivers' situational awareness regarding ODD limitations of L2 vehicles?
    - How will trust in automation change after receiving the training?

The following chapters will discuss each of the mentioned experiment in details with results and conclusion.

CHAPTER 3

EXPERIMENT 1

3.1. Phase I

The objective of this phase is to determine if drivers over-rely on automation in scenarios where transfer-of-control is critical to road user safety and, if so, what interface might better support transfer-of-control. Previous research has identified general effects of over-reliance (e.g., longer response times), but not specific details of those scenarios in which these effects are most problematic. As such, we chose three different roadway geometries where drivers need to resume control. We asked whether and how drivers transferred control when it was critical. We focused on naïve drivers (drivers who were not told about the ODD) because of numerous studies which indicate that drivers understand little about these systems (McDonald et al, 2017)

3.1.1. Method

Participants drove twice through a virtual world containing four scenarios. In one drive, participants engaged L2 system, while in the other, they drove the car manually. Thus, all participants drove both L2 and manual drives. To observe drivers' transfer-of-control behavior, drivers' foot movements were recorded. To gain insight about drivers' experience with L2 features, a set of interview questions focused on transfer-of-control, road design, and interface were designed based on twelve principles of transparency (Debernard et al, 2016). For instance, participants were asked questions such as, "Did you get surprised by the movement of your own vehicle near the curve?" , "What would you do differently if faced with this scenario in future?" and "What information do you think would be useful to present to the driver in that situation?". The interview took place right after each scenario . After conclusion of all drives, a final set of interview questions focused on need for feedback. Also, to assess drivers' situational awareness, they completed the Situation Awareness Rating Technique (SART) questionnaire (Selcon & Taylor, 1990) after each L2 drive. SART measures how aware participants perceived themselves to be during their driving performance based on ratings of understanding, supply, and demand.

3.1.1.1. Participants

Ten participants aged 20 – 54 years old (5 females and 5 males) were recruited from the University of Massachusetts Amherst campus and Amherst town using flyers and email advertisements. Average age of the participants was 27.4 years (SD = 3.07). Only individuals with a valid United States driving license who did not wear eyeglasses were included in the study.

3.1.1.2. Equipment

- Driving Simulator : A fixed-based RTI (Realtime Technologies Inc.) driving simulator consisting of a fully equipped 2013 Ford Fusion surrounded by six screens with a 330-degree field of view was used for the current study (Figure 1). The cab features two dynamic side-mirrors which provide realistic side and rear views for participants. The car's interior has a fully customizable virtual dashboard and center stack. The simulator is capable of simulating L2 drives by integrating lane centering control system and adaptive cruise control.
- Eye tracker & Video Camera : An ASL (Applied Science Lab) Mobile-Eye XG head-mounted eye tracker consisting of a scene camera, eye camera, and a small reflective

non-obtrusive monocle was utilized to monitor and record eye movements (Figure 2). Foot movement were recorded using a JVC HM40 video camera.

Figure 1. RTI Fixed-Based Driving Simulator

Figure 2. ASL MobileEye

3.1.1.3. Scenarios

Four scenarios were used to collect information regarding drivers' behavior and reactions to confusing transfer-of-control situations. Table 2 describes scenarios where three road geometries (Curve, Merge, Intersection) were considered based on previous literature (Gold et al., 2013; Seppelt & Victor, 2016). All scenarios represent situations where L2 disengaged because it reached its ODD limit and a crash could occur.

Table 2. Scenario Descriptions for Phase I

Scenario Description	Top Down View
Merge- The driver reaches the end of a four-lane road (two travel lanes in either direction). A car is also going straight in the left lane at a constant speed.	
Curve- The driver is traveling along a curved road section (one travel lane in either direction), where a truck is parked on the right side of the curved road. A car is approaching in the opposite lane.	
Intersection- The driver is approaching towards traffic signal-controlled intersection and the driver has a green light in his travel lane. A block of buildings obscures a pedestrian who is running to cross the street at the crosswalk.	
Baseline- This is a scenario in a suburban setting with no hazards.	

3.1.1.4. Experimental Design and Dependent variable

Participants drove through four scenarios (Table 2) two times: Once while engaging L2 system and once without L2 system. Ordering of the drives was counterbalanced across participants: half of the participants drove automated drives first, while the other half drove manual drives first. Each participant experienced a different order of drives in the set with automation and in the set without automation.

One dependent variable was takeover reaction of drivers, which was binary coded (Successful takeover was '1' and unsuccessful takeover was '0'). Another dependent variable was the overall SART score, which was derived using the following formula: SA = U - (D - S), where U refers to summed understanding, D refers to summed demand and S refers to summed supply (Selcon & Taylor, 1990).

3.1.1.5. Procedure

After participants gave consent, they were given basic instructions and were seated in the simulator. The eye-tracker was mounted on participants' head and their pupil position was calibrated. Next, participants were introduced to the L2 system and were shown how to engage and disengage the system. Participants then drove a practice drive and were permitted to continue when confident. Drivers were not instructed on how to behave when L2 was engaged. Participants then navigated twice through all scenarios, once with DSF engaged and once without DSF engaged. In L2 scenarios, participants drove the vehicle in manual mode for approximately one minute, prior to being alerted to engage L2 system by pressing a button on the steering wheel. A small blue LED icon on dashboard would light up each time system was engaged (Figure 3). The participants could regain manual control by applying brake or pressing the button on steering wheel. After each L2 drive, participants completed the SART (Selcon & Taylor, 1990) and were briefly interviewed. In this interview, we asked participants questions such as: “What information do you think would be useful to know about the situation on the road?”. At the end, they were interviewed again, completed a questionnaire regarding demographics and driving history, and were compensated.

One of the objectives of the study was to observe participants takeover reaction in critical situations. Therefore, there was no visual or audio feedback provided to participants regarding takeover control situations. Also, in order to observe whether participants were aware of the importance of knowing system’s status, we used a simple blue LED icon on dashboard interface, which turned on to signify that automation was engaged. In this way, we prevented bias in participants’ interview responses by not providing a preconceived design.

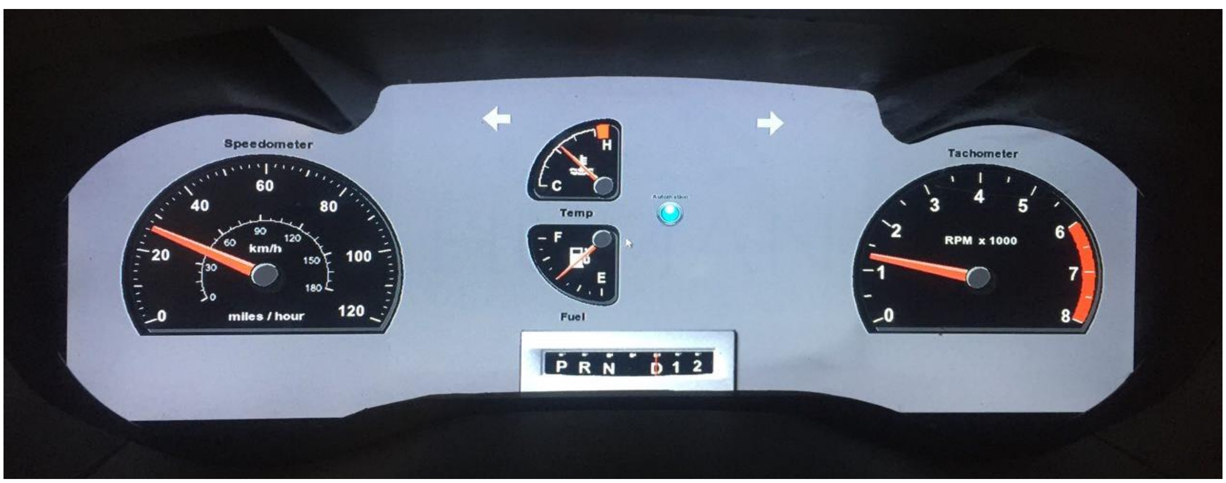


Figure 3. Original Dashboard Interface

3.1.2. Results

3.1.2.1. Over-reliance

A three-second window before the hazard was used to observe participants’ takeover reaction, similar to previous research in hazard mitigation training (Muttart, 2013). Within this window, drivers' takeover reaction was characterized by foot movement towards brake pedal or by pressing automation button. Results show that seven drivers took back control for merge and intersection scenarios and only four drivers took back control in curve scenario.

Results from SART showed that drivers' overall SART scores for curve, merge, intersection and baseline scenarios were 14.7, 19.4, 19.3 and 20.8, respectively. SART results also showed that overall score at curves was less than other scenarios, while merge and intersection scores were similar. These results further support the participants' takeover reaction results which show that they over-rely on automation (did not take back control) at curve compared to merge and intersection scenarios.

Additionally, participants' interview responses after each automated drives were gathered and categorized. Seven participants responded 'Yes' as to whether they were surprised by the car movement in curve scenario. In their responses, they expressed their expectation for the car to slow down when approaching the curve. Regarding the question on what they think would be useful information to present to drivers, three types of responses were extracted from their statements: (1) need to take back control, (2) need for feedback about L2 functions, and (3) need for feedback about road geometry. Table 3 shows difference between three scenarios in terms of participants' interview responses.

Table 3. Responses from each scenario's interview

	Number of participants (out of ten) who declared the following statements during the interview				
	Surprised by the car	Would take control sooner on a second chance	Need feedback about taking back control	Need feedback about the L2 functionality	Need information about road
Curve	7	5	4	0	5
Merge	6	6	4	6	9
Intersection	6	6	9	2	9

3.1.2.2. System Feedback

In the final interview, drivers were asked several questions about what information they needed regarding the road and automation system. For example, they were asked: "What information do you think would be useful to know about the on-road situation?". In response to this question, a participant replied: " It would be helpful to see the road's layout such as intersection, merge, etc. in advance". Another participant said "feedback about when it is not safe to use automation would be nice". In total, seven participants were interested in receiving feedback about presence of pedestrians and objects on the road and nine participants preferred feedback about road structure in advance.

In response to the question "How should information be presented (auditory/visual/tactile)?", they replied," Auditory feedback would be very helpful in a dangerous situation and visual feedback can help in minor situations". Another participant mentioned, "I would like a combination of visual and auditory, but I think Tactile feedback would make me more nervous and distracted". Regarding type of feedback, nine participants preferred to receive visual feedback, while eight preferred auditory and only two preferred tactile.

Participants were asked if they knew about the vehicle mode at all times during their drives and if yes, how they recognize the correct mode. An example response was "Yes, I knew that car was on automation mode by the vehicle's steady movement". Another person responded by saying "I know that automation was engaged since the car's speed was constant ". However, they also mentioned that they did not notice the blue LED light on dashboard. Eye tracker data showed that seven participants fixated their glance on the dashboard right after the "engage automation feature" pop-up image appeared on-screen at least once during their driving session. However, only four participants declared that they saw the blue LED light during their final interview.

To understand participants' knowledge regarding L2 vehicles, they were asked if they know how these vehicles monitor the road and why this information was necessary. Only half of the participants indicated familiarity with how automation system monitors the road and among them, only two participants mentioned weather condition impairing automation system functions. None of the participants mentioned system limitations regarding road design or when lane marking is not available (e.g. at merge sections). In total, eight participants declared that they needed information about automation system's capability. For example, one participant said, "It would be great if I could get such information so that I could analyze oncoming situations and make a better decision regarding automation disengagement".

3.1.3. Discussion

The results from first phase indicated that participants over-relied on automation for curve scenario. This might be due to drivers' failure to understand DSF functionalities at curves. Note that none of the drivers believed that they needed to know more about DSF functionalities at curves (Table 2). In general, their SART responses indicate that drivers were less situation aware at curves compared to other scenarios. Recall that in this scenario, there was a truck parked on the right and a car approaching in the opposing lane required drivers to thread their car between the car on the left and truck on the right. All drivers in manual condition slowed as they approached the truck. But DSF does not slow the driver at the curve as drivers approach the truck.

As mentioned before, participant interview responses right after each drive showed that more than half of them were surprised by car's movement and they expected differently from the system. They also declared that they would take control sooner on a second chance. This shows the mode confusion experienced by most of the participants, especially in curve scenario where only four drivers took back control. On the other hand, in final interview, seven participants declared that they need feedback about presence of pedestrians and objects on the road and nine participants were interested to receive feedback about road structure ahead of time. Based on all responses, we can conclude that it might be helpful to alert drivers regarding take back control situations.

This can be achieved in two steps: First, drivers need to be alerted that a transfer-of-control is required. This can be done by giving feedback to drivers to take back control in the form of visual, auditory, and/or tactile feedback. Second, drivers need to understand why they need to take control to become fully situation aware. This understanding could be provided by a diagram depicting alerts about change in road geometry and objects detected on the road.

Results also show that only four participants noticed the blue LED light on the dashboard (which indicated automation status), despite having glanced at the dashboard. It has been recommended that automation systems up to Level 4 should inform drivers about the system's status and limitations (Kyriakidis et al, 2017). This information can be provided by designing a more attention-grabbing display based on drivers' mental model.

To sum up, designing an appropriate interface that provides crucial information regarding safe transfer-of-control could be helpful to support drivers in their supervision and intervention role in DSF (Van den Beukel et al., 2016). This raises an argument to redesign the feedback for automation system status and also provide appropriate feedback regarding taking back control when system has reached its ODD limitations. These concerns will be considered during our prototyping and re-designing in Phase II.

3.2. Phase II

The objective of this phase of study is designing a new interface for L2 system based on phase I results. Interview responses from phase I indicated that we need to design a proper feedback system for takeover control situations along with all related information such as road geometry and also re-design feedback for automation system status. To achieve this, four design iterations have been conducted and will be explained in following sections.

3.2.1. First Design Iteration

An initial prototype was made using the dashboard interface from phase I, as seen in Figure 3. Participants responses from Phase I were extracted and aggregated to create new elements that could be featured on the initial prototype of the dashboard interface. In this process, two factors were considered: design of current vehicles, and visibility and color of display icons. The first element added was an icon depicting the automation system status. In order to design a proper LED icon similar to the design found in commercial vehicles (Cadillac, 2018; Tesla, 2019) , an illustration of a car between two lanes was hand-drawn (Figure 4). When switched on, this would give drivers a basic indication that automation system has been engaged and it will keep the car between the two lanes. The second element added was 'take over control' icon. An LED shaped like a steering wheel would develop a mental model in the driver to be concerned with the control mode of the vehicle (Figure 4). These two designs were chosen based on the design of current HMIs in commercially available vehicles such as Cadillac CT6 (Cadillac, 2018) and Tesla X (Tesla, 2019). The third element added was roadway geometry icon(s). Curved sections were considered due to two reasons: first due to the importance of curves as mentioned in previous studies (Seppelt & Victor, 2016) and second due to the observed over-reliance of participants at curve scenario in phase one. Merge and intersection were also considered based on participants' responses in phase 1 where all but one participant stated their need for feedback regarding these sections of the roadway. Three different roadway geometry icons for curve, intersection, and merge were considered based on their respective road signage (Figure 4. First Design Iteration). The fourth element added was an empty box to be filled with a proper text alert. For all the new elements, visibility, placement, and color of icons would be decided in the next design iteration.

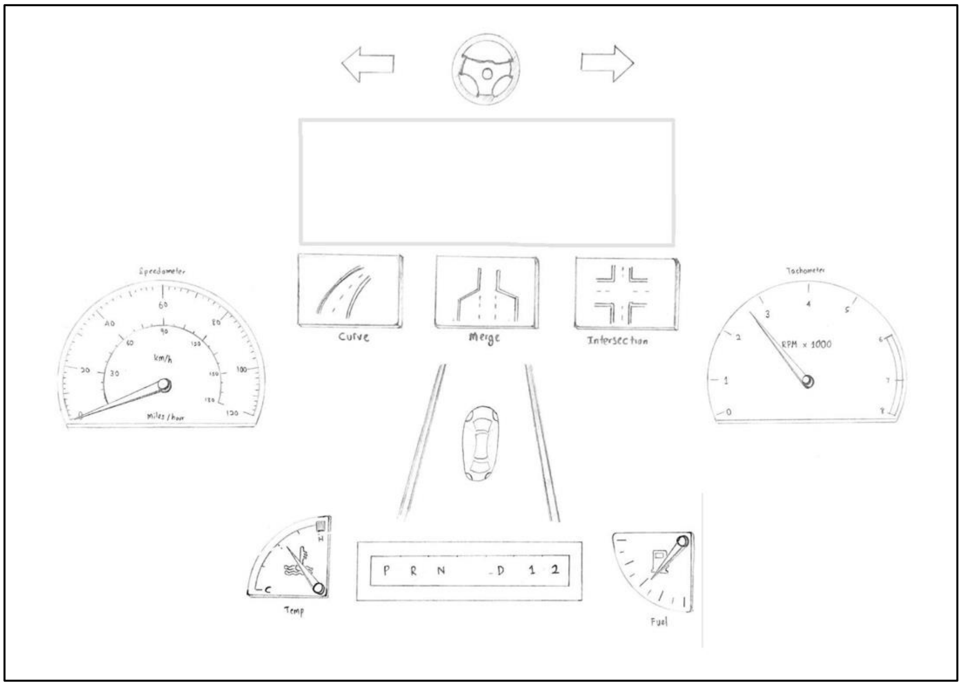


Figure 4. First Design Iteration

3.2.2. Second Design Iteration

In this iteration, the design of the prototype dashboard interface was modified based on the results of individual co-design sessions with 10 participants.

3.2.2.1. Participants

Ten participants (aged 20 – 54) were recruited from the same area as Phase I. The average age of participants was 27.4 years. Only individuals with a valid United States driving license were included in these sessions.

3.2.2.2. Equipment

A JVC HM40 video camera was used to record the discussion with participants as well as their prototyping suggestions such as placement or redesign of icons. The camera was positioned in a bird's eye view to capture the prototype in full view.

3.2.2.3. Procedure

All participants completed a 45-minute individual session. In these sessions, after participants gave their consent, they were then interviewed with series of questions targeting takeover request, automation system status, road geometries, and objects detected on the road. For example, for takeover request, they were asked the following two questions: “Do you need informative visual feedback on dashboard to take over control from the system?” and “Do you need labeling in addition to visual feedback?”

Following their responses, they were then presented with a cut out of the steering wheel icon and asked the following question: “If this object’s shape lights up, what would that indicate in your opinion?”. The purpose of the icon was then explained, and the next question was asked: “What color do you prefer for this item? ”. They were then asked to relocate the item to their most convenient choice of place on dashboard and also asked for suggestion to design better feedback for a takeover request for which they were given the opportunity to hand-draw their suggestions or alternative ideas.

A similar procedure was followed for ‘automation system status’, ‘road geometries’ and ‘objects detected on the road’. Figure 5-6 shows an example of a participant’s’ final design sheet indicating their preference for location and design.

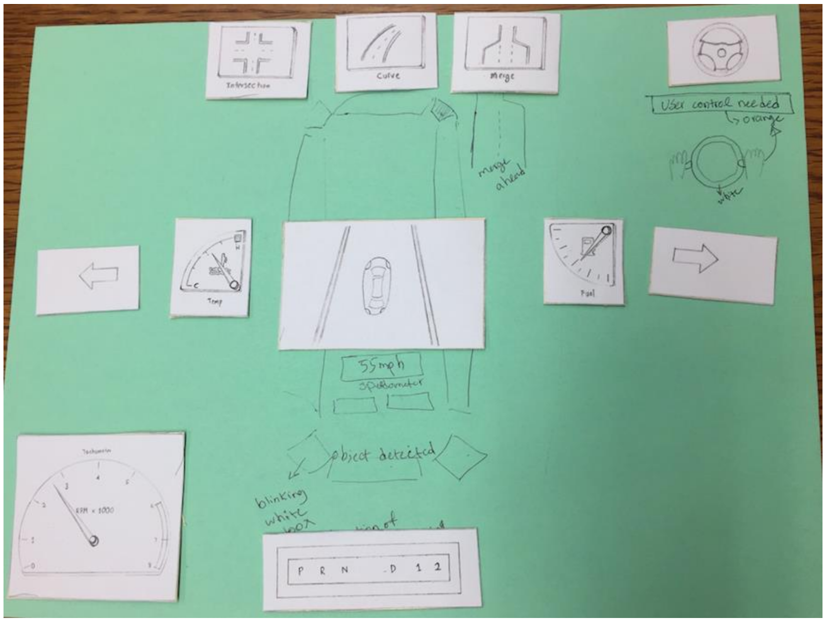


Figure 5. An example of a participant's final design sheet

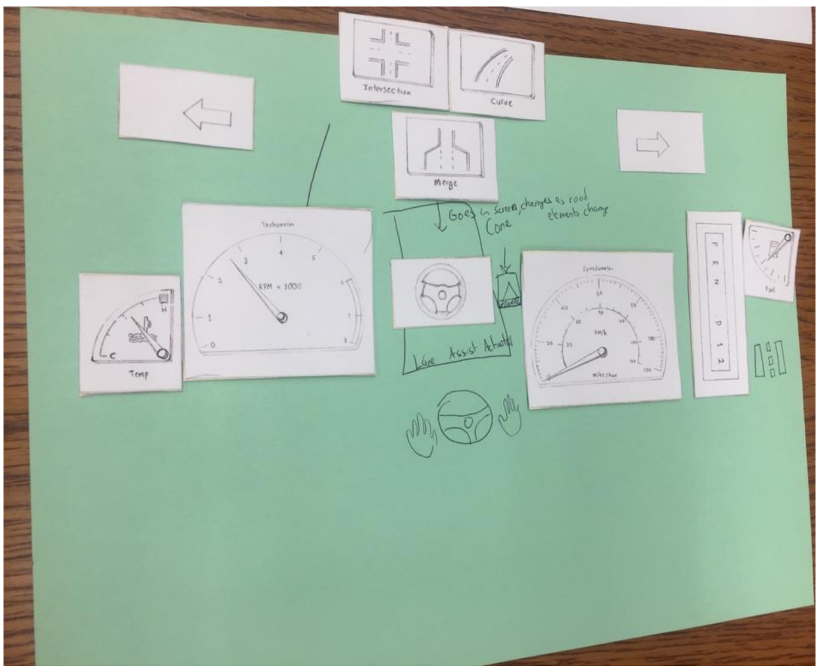


Figure 6. Another example of a participant's final design sheet

3.2.2.4. Results

Participants responses during co-design sessions and interview were aggregated. Participant responses to questions regarding automation system status show that all participants were in agreement about their need to know about vehicle's status. They all understood the purpose of the display icon correctly (automation engaged when LED icon lights up and automation disengaged when icon is not lit). Also, they were all in agreement that "car between two lanes" icon is suitable to understand lane centering system. Seven out of ten participants indicated that there was no need for icon labeling.

In response to the question "Do you need informative visual feedback on dashboard to take over control from the system?", one participant replied, "Yes, I would very much prefer audio feedback, but combining it with visual feedback may be most helpful if I'm listening to music". In total, based on their responses, eight participants indicated that they needed visual feedback. Five participants indicated that they required a combination of auditory feedback and visual feedback. As a follow-up question, they were asked if they preferred labeling for takeover control icon on dashboard. In response, half of the participants said that they preferred the icon with a text label. When asked for redesign suggestions, several participants mentioned that the steering wheel icon alone did not signify taking back control action. There was a common redesign suggestion by half of the participants to redesign the icon by adding hands hovering over steering wheel.

For questions about road geometry, participants responses showed that all understood the purpose of display icon correctly. Most participants declared that "when LED icon lights up, the displayed road geometry is coming up ahead". When they were asked about their preference for feedback type, nine participants indicated that they preferred visual feedback for information regarding roadway geometry. When asked "Do you need a label for any roadway icons?", seven of the participants indicated that there was no need to label the icon, saying that icons were informative on their own. For example, one participant replied saying "I think the icon is easy to understand and adding a label would make my dashboard crowded". As a common suggestion, half of the participants preferred that the three roadway geometry icons appear in the same location on the dashboard (above 'automation system status' icon) when prompted. Two participants pointed out that they preferred the merge icon to be more consistent with its road sign i.e., one-sided merge.

Finally, for questions regarding 'object detected on the road', responses showed that nine participants needed visual feedback while only two preferred auditory feedback as well. This was followed by asking participants to suggest icon shapes, to which four participants drew a traffic cone-shaped icon to depict 'object detected'. Other participants also drew similar stationary objects such as a large rock or a cube. When asked if they need icon labeling, one participant mentioned, "Yes, I think having a label saves me time to recall the icon's meaning". In total, eight participants preferred the text label 'object detected'. One participant suggested to have two types of icon for object on the road, one dynamic icon and one static icon, saying "I prefer if the icon can also show me if the object detected is stationary or moving, so it would make sense to have two types of the icon, one dynamic and the other static".

The first iteration design was updated based on results from all co-design sessions. Figure 7 shows the design after second iteration.

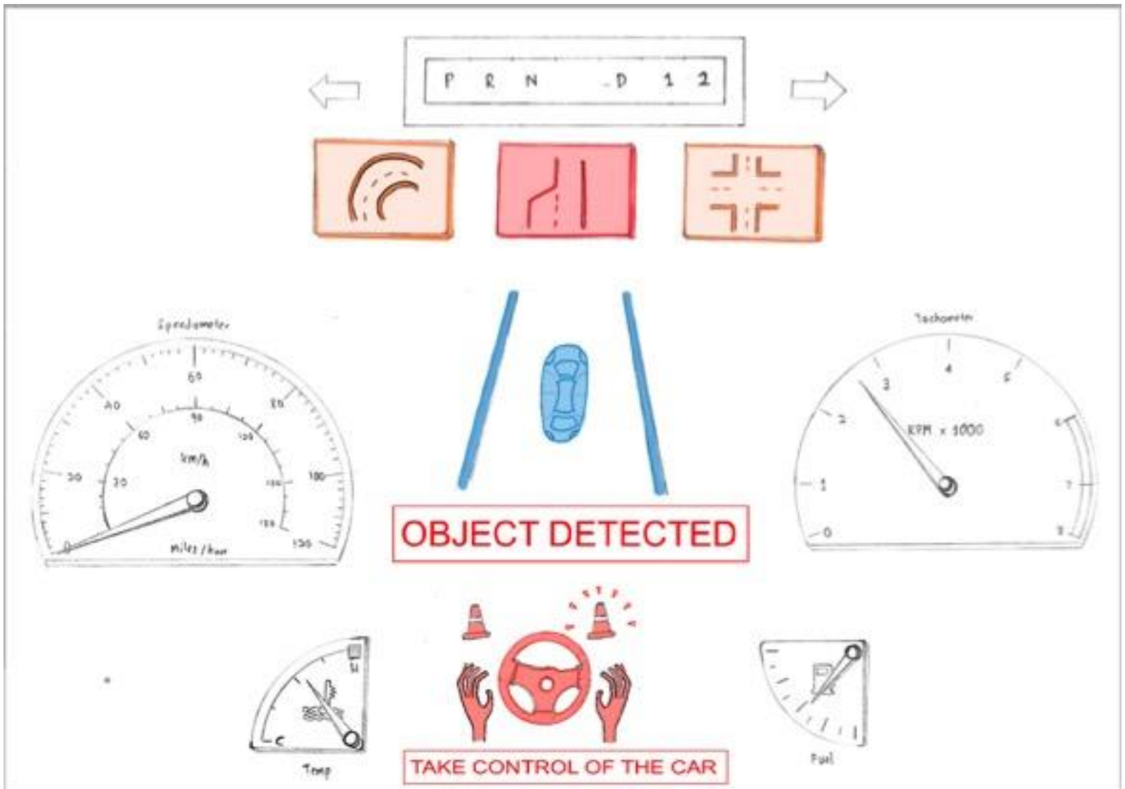


Figure 7. Second Design Iteration

3.2.3. Third Design Iteration

In this iteration, the designed prototype from second iteration was applied to dashboard of the simulator cab (Figure 7, 8a, 8b). This was followed by a heuristic evaluation by four human factors specialists. The analyses were performed in isolation to suppress bias across users as well as to increase the number of independent heuristic violations discovered as suggested by previous studies (Nielsen, 1993). The heuristic evaluation was conducted for three dashboard interface designs:

1) Original Dashboard: Dashboard interface used in Phase 1 (Figure 3)
2) Basic Dashboard: Simpler version of new dashboard design from second iteration, excluding road geometry and object detected icons (Figure 7)
3) Advanced Dashboard: Dashboard design from second iteration (Figure 8a, 8b)

The difference between basic and advanced dashboard is that basic dashboard only provides basic feedback such as take back control request and system status, similar to HMI design of commercially available vehicles such as Cadillac Super Cruise (Cadillac, 2018). Advanced dashboard provides additional feedback along with the ones featured on Basic dashboard, where information regarding take back control situations will be presented prior to take back control requests. We decided to present these two interfaces separately to investigate the issues concerning the Basic dashboard (available in commercial vehicles) as well as Advanced dashboard (conceptualized and designed in this study).

3.2.3.1. Participants

Four human factors specialists (two female and two male) were selected. One was an assistant professor (9 years of experience in Human Factors) and other three were doctoral students (3 years of experience in Human Factors). All were from the Mechanical and Industrial Engineering Department at University of Massachusetts Amherst.

3.2.3.2. Procedure

At the beginning of heuristic evaluation, four participants were introduced to usability heuristics as introduced in Nielsen (1993). Presenting pictures from all dashboard design interfaces (Figure 3,8,9,10), the purpose of three dashboard interface designs were explained to them. They were asked to individually provide a list of issues for each dashboard interface design in isolation. Their individual responses for each interface were collected, duplicate issues were removed, and a final master list of issues was created for each dashboard interface. Each participant then received a copy of the master list and asked to allocate a severity rating to each issue.

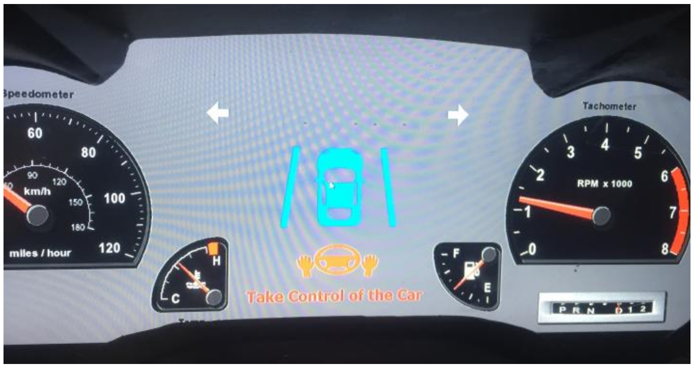


Figure 8. Basic Dashboard (Second iteration)

Figure 9. Advanced Dashboard for object detected on the road (Second iteration)

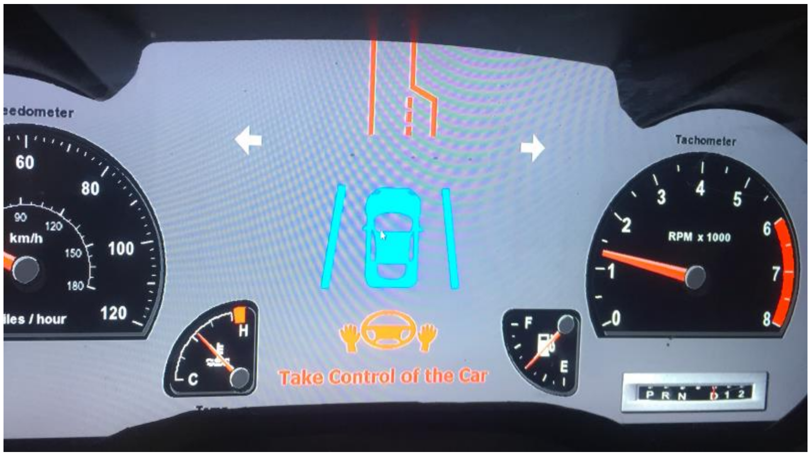


Figure 10. Advanced Dashboard for road geometry (Second iteration)

3.2.3.3. Results

The average severity rating was calculated for each issue based on all participants response. Table 4-6 shows the most severe issues for each of the dashboard interface designs.

Table 4. The heuristics, violations, and severity ratings for Original Dashboard

Heuristics	**Issues**	**Average severity rating**
Visibility of the system	The interface does not provide enough information about the automation features (lane keeping system, cruise control,..)	4.25
Match between System and Real world	The blue light is a very ambiguous way to show the automation status (on/off). It might be hard for the drivers to connect a simple LED light to the automation system.	4.5
Recognition and Recall	There is no information to help the drivers recall to take control from the car (as specified in the owner's manual)	4.5
Error Prevention	There are no error messages (to help the drivers recognize or prevent the errors)	4.25

Table 5. The heuristics, violations, and severity ratings for Basic Dashboard

Heuristic	**Issues**	**Average severity rating**
Visibility of the system	The interface does not provide any reasoning or information about why the drivers need to take control of the car	4.25
Match between System and Real world	The important ‘take control’ message is not placed in the center of the display (where the most important information is), but rather appears at the bottom of the display	4
Recognition and Recall	The dashboard in itself may not be sufficient to engage the driver and may require audio cues for the take back control feedback.	4.5

Table 6. The heuristics, violations, and severity ratings for Advanced Dashboard

Heuristic	**Issues**	**Average severity rating**
Match between System and Real world	The important 'take control' message is not placed in the center of the display (where the most important information is), but rather appears at the bottom of the display	4
Recognition and Recall	The dashboard in itself may not be sufficient to engage the driver and may require audio cues for the take back control feedback.	4.5

Result from heuristic evaluation for Original Dashboard shows that blue LED light does not have proper visibility and it does not provide effective feedback about system features. The issue regarding the blue LED light has been resolved in the simple and complex dashboard design in previous design iterations.

For Basic Dashboard, the first issue was related to the system visibility with regards to the reasoning behind the take back control request. This issue has been addressed in Complex Dashboard for four different types of situations, three regarding road geometry and one regarding object detected on the road. The second issue for Basic Dashboard was related to placement of the take back control feedback. This issue was addressed in the final design iteration, by placing take back control feedback in the center of the dashboard. The third issue of Basic Dashboard was regarding the recognition of the feedback system. It was suggested to provide audio beeps with addition to the visual feedback for the take back control feedback. The second and third issues were similar for the Advanced Dashboard as well. Both of these issues were addressed in the final design iteration.

The original dashboard was not modified in order to be used as a baseline for testing the Basic and Advanced dashboard in the third phase of the study.

3.2.4. Fourth Design Iteration

In this iteration, five human factors specialists drove through the same scenarios, following same procedure as in Phase 1, but this time with both basic and advanced dashboard interfaces. Their final feedback regarding the interface design was collected and roadway geometry elements were modified to increase their visibility on the dashboard. One specialist also pointed out that automation status icon (blue car between two lines) was only half visible, obscured by the steering wheel. Hence, the placement of icons was also modified to accommodate anthropometric factors. Moreover, another specialist suggested adding an additional beep to all of the object detected and road geometry related to visual feedback. Their argument was that an auditory beep would serve as redundancy for drivers to get information provided on dashboard. The beep for take back control feedback was replaced to an audio message with a female voice. This was done to distinguish both types of audio feedback and emphasize importance of take back control feedback. The final Basic Dashboard design is shown in figure 11. The advanced dashboard interface design is shown in figure 12-15.

Figure 11. Basic Dashboard (Fourth iteration)

Figure 12. Advanced dashboard showing the object detected icon (Fourth iteration)

Figure 13. Advanced Dashboard showing a curve ahead (Fourth iteration)

Figure 14. Advanced Dashboard showing an intersection ahead (Fourth iteration)

Figure 15. Advanced Dashboard a merge ahead (Fourth iteration)

3.3. Phase III: Testing Designed Interfaces

The objective of this phase was to test the interfaces for designed in Phase II. To achieve this, seven scenarios were designed, and three participant groups drove through all scenarios. One group was exposed to the Original Dashboard, a second group to the Basic Dashboard and a third group to the Advanced Dashboard. All participants drove six scenarios in L2 mode and one scenario in L0.

3.3.1. Method

3.3.1.1. Participants

A total of 42 participants (aged 20 – 54) were recruited from the same area as previous phases. The average age of participants was 25.73 years (SD = 4.37). The sample size included 30 males and 12 females. Only individuals with a valid United States driving license who did not wear eyeglasses were included.

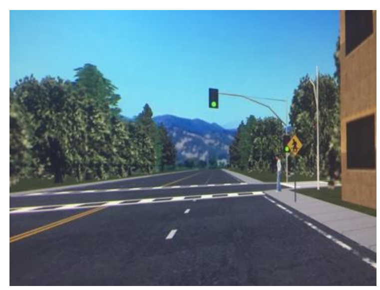
3.3.1.2. Equipment

The equipment used in this phase was similar to that from phase I.

3.3.1.3. Scenarios

Seven scenarios were designed to investigate drivers' behavior and take back control reactions in three groups (Original Dashboard, Basic Dashboard, and Advanced Dashboard). Table 7 describes scenarios which were designed based on common human-automated vehicle conflict situations reported in literature (Seppelt & Victor, 2016).

Table 7. Scenario Descriptions for Phase III

No.	Scenario Description	Image
1	The driver reaches the end of a four-lane road (two travel lanes in either direction) which merges onto a two-lane road (one travel lane in either direction). There is a car following behind the driver into the merge.	
2	The driver is traveling along a curved road section (one travel lane in either direction), where a truck is parked on right side of the curved road section before a crosswalk. The truck is partly jutting onto the road obscuring a pedestrian.	
3	The driver is approaching towards traffic signal-controlled intersection (two travel lanes in either direction) with a green light in the travel lane. A block of buildings obscures a pedestrian who is running to cross the street at the crosswalk.	
4	The driver is approaching towards a traffic signal-controlled intersection (one travel lane in either direction) with a green light in the travel lane. There are no vehicles or pedestrians in the vicinity.	

5	The driver is approaching a stop sign controlled intersection (one travel lane in either direction) while following a car. The following car abruptly stops at the stop sign and proceeds to turn right.	
6	This is a scenario within a suburban setting with no hazards.	
7	The driver is approaching towards a traffic signal-controlled intersection (one travel lane in either direction) with a green light in the travel lane. A car in the opposite lane across the intersection briefly signals left before abruptly taking a left turn, driving across the driver's path.	

3.3.1.4. Experimental Design and Hypothesis

In this study, a between design experiment was used and participants were randomly assigned to one of three groups - Original Dashboard, Basic Dashboard, or Advanced Dashboard. They were asked to drive through seven scenarios shown in Table 6. They drove through scenarios 1 - 6 while engaging the L2 system and drove scenario 7 in L0 mode. The ordering of drives was counterbalanced across participants in each group using the Balanced Latin Square method (Williams, 1949).

First, we hypothesize that when compared to the Original Dashboard, the Basic and Advanced Dashboard will help participants effectively take back control from the L2 system when needed. Also, user satisfaction will be higher for the Basic Dashboard compared to Original Dashboard and similarly, user satisfaction for Advanced Dashboard will be higher compared to Basic Dashboard. Second, we hypothesize that presenting roadway information regarding take back control (in Advanced Dashboard) reduces reaction time compared to Basic Dashboard, which only presents take back control requests. The first and second hypothesis were examined for scenario1 - 4 shown in table 6. Third, we hypothesize that while drivers' situational awareness is higher during the manual drive compared to automated drives (Featuring Original Dashboard), there will be smaller difference between situational awareness of drivers in manual and automated drives (Featuring Basic and Advanced Dashboard). The third hypothesis was examined for scenario 5 and 7 shown in table 6.

Note that participants in the Advanced dashboard group received feedback regarding the road geometry and objects on the road prior to receiving takeback control requests. Take back control feedbacks were presented 5 seconds before hazards for both the Advanced and Basic dashboard groups (Scenario 1,2,3,5). Feedback regarding road geometry (scenario 1,2,3,4) and object detected (scenario 5) were presented 8 seconds before the hazards for the Advanced dashboard group.

3.3.1.5. Procedure

After participants gave their consent, they were randomly assigned to either the Original, Basic or Advanced Dashboard groups. The same procedure as phase I was employed to run participants. All participants drove through seven scenarios. Participants were asked to drive scenario 1-6 (see Table 6) while engaging L2 system, and scenario 7 manually. For the Original Dashboard group, a small blue LED icon on the dashboard would light up each time the L2 system was engaged (Figure 3). For Basic and Advanced Dashboard groups, an LED icon of a car between two lanes would light up each time the system was engaged (Figure 9-10d). In order to compare situational awareness of drivers in manual and automation mode, participants were asked to complete the SART questionnaire, once after scenario 5 and once after scenario 7. At the end, to evaluate participants' satisfaction of each dashboard design, the QUIS questionnaire was used (Chin, Diehl, & Norman, 1988).

3.3.1.6. Dependent and Independent Variables

One dependent variable similar to phase I, was drivers' takeover reaction, which was binary coded (Successful transfer of control as scored '1' and unsuccessful transfer of control was scored '0'). The second dependent variable was takeover time to hazard i.e., the time interval at which drivers take back control up until the critical event. Takeover time to hazard was used in previous study as drivers hazard avoidance measurement in transfer of control situation while driving automated vehicles (Van den Beukel et al., 2016). The first and second dependent variables were examined for scenario 1-3. The third dependent variable was overall SART score, which was calculated similar to Phase I. Other dependent variables considered in this study were attributes related to QUIS questionnaire - overall reaction rating, Capability rating, Screen rating, Terminology and Usability rating of the dashboard interface. The independent variables were dashboard design (Advanced, Basic, Original) and scenario (Table 6).

3.3.2. Results

3.3.2.1. Take Back Control Events

For descriptive purposes, the percentage of participants who took back control in each dashboard group was calculated for scenarios 1-4 and is shown in Figure 16. In all scenarios, the percentage of successful take back control was highest in the Advanced dashboard group compared to the Basic and Original Dashboard groups. In total, the percentage of participants who successfully took back control on time for scenarios 1-4 were higher for Advanced Dashboard group (81.25%) when compared to Basic Dashboard group (62.5%) and Original Dashboard group (18.75%). Participants in the Basic Dashboard group took back control 23.07% less than Advanced Dashboard group, and 70% more than participants in Original Dashboard group.

Note that unlike scenarios 1-3, for scenario 4, no hazard materialized. Hence, participants in Basic dashboard group did not receive any “take back control” message through the dashboard and participants in the Advanced dashboard group were only presented with road geometry on the dashboard. Therefore, as presented in Figure 16, while 35.72% of Advanced dashboard group participants took back control from the car in scenario 4, no participants from the Basic and Original dashboard groups took back control in scenario 4.

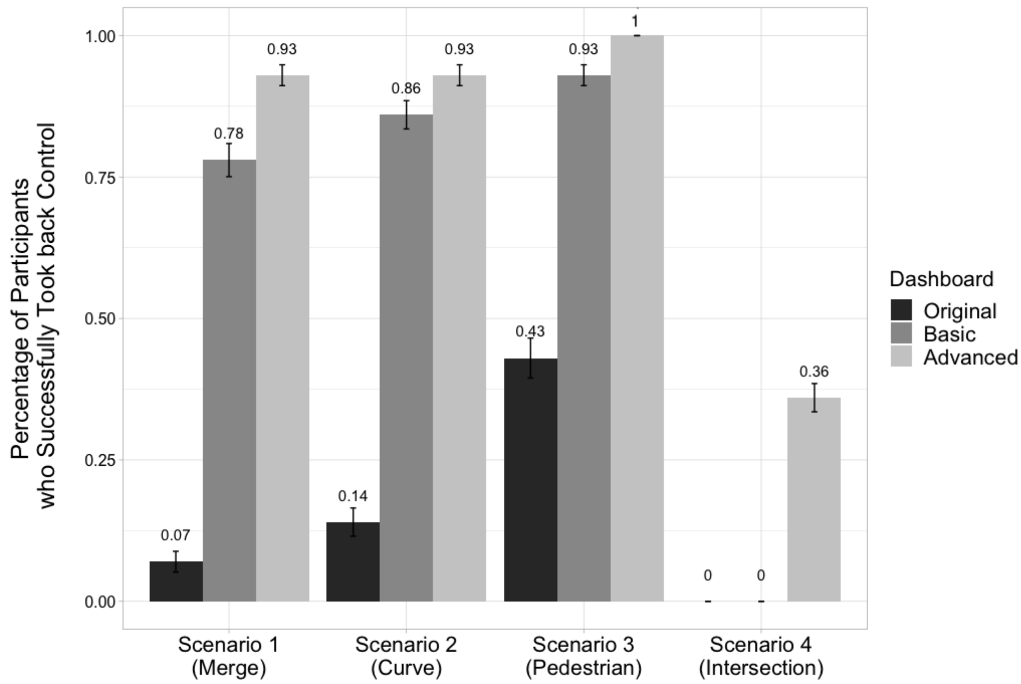


Figure 16. The percentage of participants who successfully took back control for each group

To determine whether the effect of dashboard was significant for scenarios 1-3, a logistic regression model within GEE framework was used. Here, dashboard (Advanced, Basic, Original) was included as treatment, and scenarios were included as repeated measures. Data analysis showed a significant main effect of treatment (Wald Chi-Square = 45.055, p-value < 0.001).

To investigate take back control action of participants for scenarios 1-3, the time which elapsed between when drivers took back control and when the critical event was reached takeover time to hazard was calculated for each group (Advanced, Basic and Original dashboard group). Figure 17 shows the average time calculated for each group scenarios 1, 2, and 3. A 3 (dashboard) × 3 (scenario) factorial ANOVA was performed. The result showed that there was a significant main effect of dashboard ($F(2, 117)$ =

125.895, p-value < 0.001). To investigate which of the dashboard were significantly different from each other, a Bonferroni post hoc analysis was performed, and results showed that there was a significant difference between all combinations of dashboard (Advanced vs Basic, Advanced vs Original, and Basic vs Original).

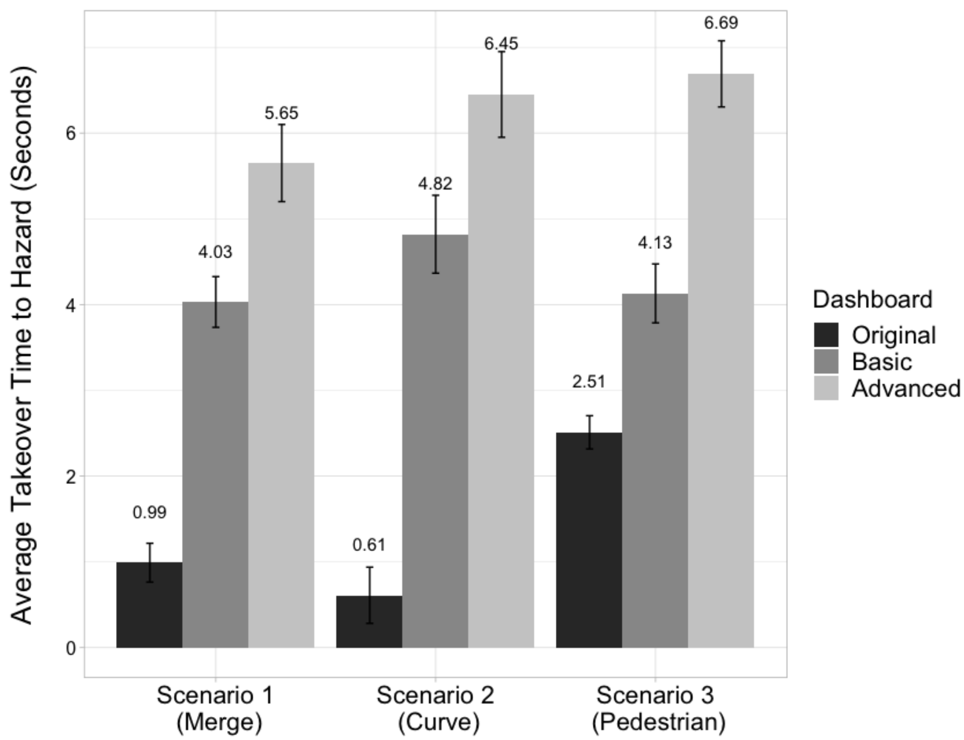


Figure 17. Average Takeover Time to Hazard for each dashboard design

3.3.2.2. Situational Awareness

The mean overall SART scores for scenarios 5 and 7 for each dashboard group were calculated. The results showed that the average overall SART score was highest in the Advanced Dashboard group (Mean = 23. 07, SD = 0.14) compared to the Basic (Mean = 20.82, SD = 1.25) and Original Dashboard (Mean = 17.61, SD = 4.25) groups. Figure 18 shows the mean overall SART scores for each scenario in each dashboard group. Note that on an average the participants' overall SART score was higher for the manual drive in scenario 7 (Mean = 22.38, SD = 0.59) compared to the L2 drive in scenario 5 (Mean = 18.62, SD = 3.96). However, due to the difference between scenario 5 and 7, i.e., having a car stop in front of the driver (scenario 5) versus having a car from the opposing lane turn in front of the driver (scenario 7), one cannot be sure whether the difference between the SART scores at the two scenarios was observed due to the usage of L2 systems in scenario 5 or the difference of the hazardous situation in the two scenarios.

Considering the difference between the two scenarios, to determine any significant difference between mean overall SART scores in each dashboard groups, a one-way ANOVA analysis was conducted twice (separately for each scenario): once for the L2 drive (scenario 5) and once for the manual drive (scenario 7). Results show that there was no significant difference between dashboards for the manual drive in scenario 7 ($F (2, 39) = 0.166$, p-value > 0.05). However, there was a significant difference between dashboard group for the L2 drive in scenario 5 ($F (2, 39) = 6.433$, p-value < 0.05). To investigate which of the dashboards were significantly different from each other for the L2 drive (scenario 5), a Bonferroni post hoc analysis was performed. The results showed that mean overall SART score for the Advanced Dashboard group was significantly higher than that of the Original Dashboard group (p-value < 0.01). However, there was no significant difference between Advanced and Basic Dashboard groups.

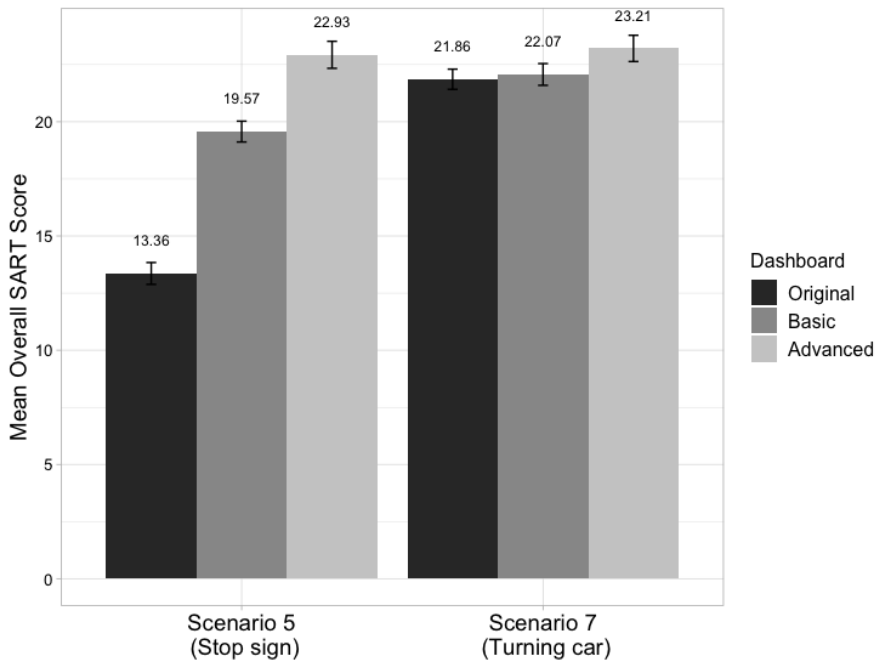


Figure 18. Average overall SART scores for each dashboard design

3.3.2.3. User Interface Satisfaction

The average rating of participants in each dashboard group for each of the five QUIS attributes (Capability, Screen, Terminology, Usability, and Overall) are presented in Figure 19. As Figure 19 shows, the values were always highest for Advanced Dashboard group, followed by Basic Dashboard group and then Original Dashboard group. On average, participants' rating for the five QUIS attributes was highest in the Advanced Dashboard group (Mean = 7.066, SD = 0.428) compared to the Basic (Mean = 6.220, SD = 0.385) and Original Dashboard (Mean = 4.304 SD = 0.738) groups.

To investigate the effect of different dashboard designs on five different QUIS attributes, a MANOVA analysis was conducted. The results from the MANOVA showed that there was a significant effect of dashboard in all five QUIS factors: Screen: $F(2, 39) = 10.81$, p-value < 0.001; Terminology: $F(2, 39) = 7.98$, p-value < 0.001; Capability: $F(2,39) = 9.26$, p-value < 0.001; Usability: $F(2, 39) = 14.26$, p-value < 0.001 and Overall Reaction of participants: $F(2, 39) = 15.33$, p-value < 0.001.

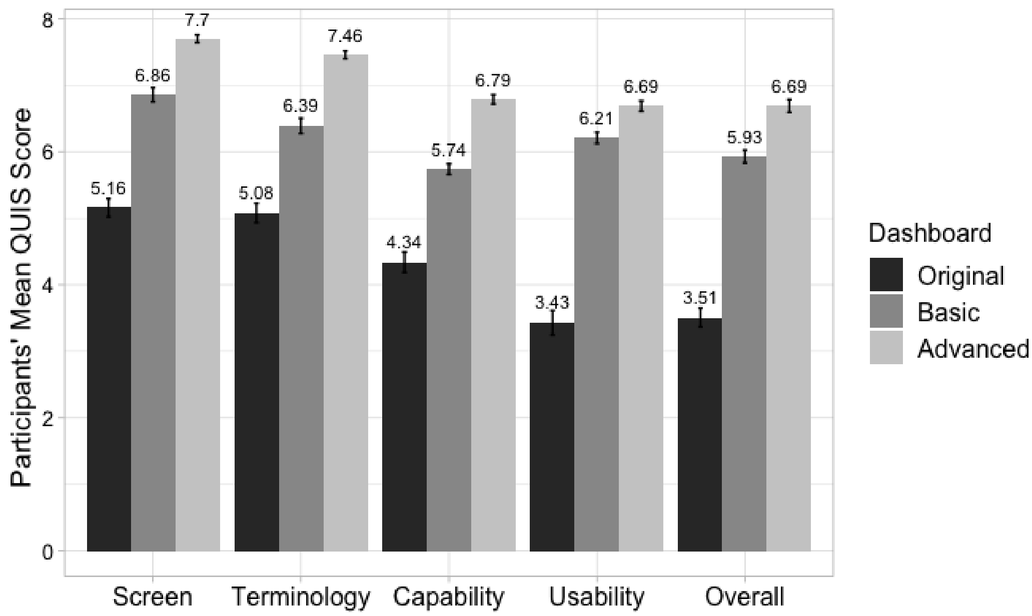


Figure 19. The average QUIS score for each dashboard design

3.4. Conclusion

This study aimed to design and test a new driver-centered HMI interface which will support drivers in their understanding of L2 vehicle status and aid them in safely retrieving control when needed as suggested by Hoc et al (2009). To achieve this, three phases were carried where the first phase tested the drivers performance in L2 vehicles while driving in different scenarios using the Original Dashboard. In the second phase, the original dashboard interface was modified through four design iterations, resulting in Basic and Advanced Dashboards. The third phase of the study tested these in-vehicle interfaces (Basic Dashboard and Advanced Dashboard) in comparison to the Original Dashboard.

Results from Phase I showed that participants over-relied on L2 system particularly at curve scenario. This issue has been pointed out in previous studies (Parasuraman & Riley, 1997b) particularly in context of automated vehicles (Boelhouwer et al, 2019). As potential solutions, it has been suggested that utilizing approprate visual and auditory feedback systems can help drivers to recognize failures of automated systems (Bainbridge, 1983) and calibrate their trust based on system capibilities (Helldin, 2013) and take back control when required (Lau et al, 2018; Van den Beukel et al., 2016). The interview responses of the participants in phase I of the current study indicated that they were aware of the need for a better feedback system which would provide more information regarding system status and on-road situations. They particularly requested audio and visual feedback regarding road geometry and status of the system.

In the second phase, an initial dashboard prototype was provided based on participants' responses in Phase I. Next, individual co-design sessions were conducted with participants to assess their understanding of the suggested designs and gain their suggestions regarding shape, size, and placement of dashboard elements. They were also given a chance to add any other objects and feedback on the dashboard regarding the L2 system. The design was then improved through a heuristic evaluation and pilot testing. Three dashboard interfaces (Original Dashboard, Basic Dashboard, Advanced Dashboard) were then prepared to be tested in the final phase. It should be noted that in the new dashboard designs, both participants needs mentioned in phase I and II, and also three challenges of interface design for L2 vehicles mentioned in previous studies have been addressed. First challenge was mode confusion (Kyriakidis et al., 2017) which addressed by providing an informative presentation of system status through an LED icon (car between lanes). Second challenge was take-back control request delivery (Banks et al, 2018) which was addressed by redundant audio and visual feedback to ensure optimal take-back control actions when needed (Basic and Advanced Dashboard). Third challenge was to revert driver attention back towards hazardous areas (Blanco et al., 2015). This was achieved by providing participants with road geometry and object detected feedback (combination of LED icons and beep) which helped the drivers to be alert and revert their attention towards the hazards ahead.

In third phase, the effect of new dashboard designs on participants' performance and satisfaction was investigated. These results shows that, despite the significant positive effect of Basic Dashboard, Advanced Dashboard was more effective in terms of helping drivers take back control in a timely manner. Note that in scenario 4 where there was no take back control message, none of the participants in the Basic and Original dashboard groups took back control, and only 36% of participants in the Advanced Dashboard group managed to take back control. This shows that while showing information regarding road geometry increased the number of successful take back control for participants in Advanced Dashboard group compared to Basic and Original Dashboard groups, 58.3% of participants in Advanced Dashboard group still did not take back control while approaching the intersection. Considering the dynamic nature of intersections and L2 systems' limitations, failing to take back control (e.g., continuing with the same speed while maintaining same lateral position) at intersections could result in drivers compromising their safety. For example, many ACC systems may not detect the sudden appearance of pedestrians or vehicles on the roadway (Tesla, 2019) and in many others, system may not brake for a vehicle it has never detected as moving (Cadillac, 2018). This issue was not observed in scenario 3 where participants received take back control feedback prior to intersection in both Basic and Advanced dashboard groups. The results showed that participants took back control most of the times when they were presented with take back control feedback prior to the intersection in scenario 3. The performance was slightly better for Advanced Dashboard group where they received road geometry feedback in addition to take back control feedback, when compared to those in the Basic Dashboard group who only received a take back control feedback.

To further investigate take back control action of participants, for scenarios 1-3, takeover time to hazard for each group was analyzed. The results from current study showed that participants in the Advanced Dashboard group took back control sooner (6.4 seconds) than participants in Basic Dashboard (4.1 seconds) and Original Dashboard groups (1.5 seconds). As mentioned earlier, many participants in the Original Dashboard group did not take back control in the mentioned scenarios, and those who did were late compared to participants of other dashboard groups. This may raise safety concerns for Original Dashboard group which presented no take back control feedback or any additional information about on-road hazard situations. A previous study by Mok et al (2015) showed that most of the participants who took back control from automation two seconds or earlier leading to the hazards could not negotiate on-road hazard situations safely. However, those who took back control five and eight seconds leading to the hazards were able to safely negotiate on-road hazard situations (Mok et al., 2015).

Late transfer-of-control by participants may be of particular importance when considering those scenarios involving pedestrian hazards (Scenario 2 and scenario 3). In these scenarios, drivers need to anticipate pedestrians as well as take back control from the car. Results from Samuel et. al (2016) showed that transfer-of-control timing is important for drivers of L2 systems in pedestrian involved hazard situations. Results from their study showed that distracted drivers who took back control four seconds leading to the pedestrian-involved hazards only anticipated 33% of hazards, while this rate was almost twice (60%) when they took back control six seconds before the pedestrian hazard (Samuel et al, 2016). In the current study, while participants in Original Dashboard group did not take back control in many instances and participants in Basic Dashboard group took back control approximately 4 seconds leading to the pedestrian hazard (scenario 2 and 3) , participants in Advanced Dashboard group took back control sooner than six seconds leading to the pedestrian hazards for scenario 2 and 3.

Another aspect investigated in this study was the situational awareness of the drivers. Previous studies showed that interface design for automated car can significantly effect the drivers situational awareness in transfer of control situations (Van den Beukel et al., 2016). Results from the current study showed that the participants in the Advanced Dashboard group were more situationally aware than the participants in the Basic and Original Dashboard groups on an average while in driving in L2 mode. These results are aligned with van den Beukel et al (2016) study which showed that using combination of visual and auditory feedback increases situational awareness while driving in automated vehicles (Van den Beukel et al., 2016). Participants in Original Dashboard group had the lowest situational awareness among three groups while driving in L2 mode. This shows that driving in L2 mode without an appropriate HMI can decrease situational awareness of the drivers as previous studies also indicated (Endsley, 1999; Merat & Jamson, 2009b). There was no difference in drivers situational awareness while driving in manual mode for all three groups. This shows that participants in three group had similar situational awareness while driving in manual mode thereby ruling out a potential confound where the situational awareness of the drivers would be different due to induvial differences of participants in each group.

To investigate user satisfaction, the QUIS was used. This questionnaire was used previously for similar studies to quantify participants acceptance and satisfaction regarding partially automated vehicle (Hjälmdahl et al, 2017). The results from the QUIS for the current study showed that participants in the Advanced Dashboard group had the highest satisfaction scores for all five factors of the QUIS questionnaire. Among all factors, Usability had the highest improvement from Original Dashboard to Advanced Dashboard with 3.55 improvement in average score of participants.

It could be noted that unlike Advanced Dashboard design, variants of the Basic Dashboard design are available in commercial L2 vehicles. The results from this experiment showed that the drivers' performance could be improved by providing additional information (e.g., roadway information). Hence it might be useful to explore methods to improve drivers' performance in current L2 vehicles. Training the drivers to understand the ODD limitations of L2 vehicles particularly regarding road geometry and objects on-road can be helpful to prepare drivers for oncoming take back control situations.

CHAPTER 4

EXPERIMENT 2

Result from experiment 1 showed that drivers takeover performance was improved by providing information regarding road geometry in advance to takeback control request. However, as mentioned earlier there are no dashboards similar to advanced dashboard available in current L2 vehicles. Moreover, there are more scenarios where L2 systems are not capable of detecting hazard (e.g. bicyclist, pedestrian, etc.) and hence there is no way that L2 systems can provide feedback to drivers regarding those situations. As results from experiment 1 showed, when there was no take back control feedback prior to an intersection, none of the participants took back control from the car. Considering the ODD limitations of L2 vehicle (e.g. cannot detect pedestrian, bicyclist, crossing traffic) and dynamic environment of intersections, this might cause crucial safety issues. This example from experiment 1 shows that at more complex situations where the L2 vehicle do not detect or predict hazards, it is up to drivers to perceive the situation properly and take back control from the automation system.

As a solution to this issue, training has been suggested by many studies to help drivers to gain knowledge about limitations and capabilities of automated vehicles (Beggiato et al., 2015; Forster et al., 2019; Koustanaï et al., 2012; Payre et al., 2016). Past studies showed that training was helpful to improve drivers performance and knowledge about the automation. For example Koustanai et al (2012) showed that training improved drivers performance while using forward collision warning (FCW) system (Koustanaï et al., 2012). Payre et al (2016) showed that training drivers for using highly automated vehicles (capable of overtaking, accelerating, braking and interacting with other vehicles) improved their response time to emergency take back control situation (Payre et al., 2016). Forster et al (2019) showed that interactive tutorial helped drivers to understand lane keeping system more accurately comparing the owner's manual (Forster et al, 2019).

Despite the important role of training mentioned in previous literature, only a few training programs for L2 vehicles have been designed and tested. Most of the studies depended on self-reported questionnaire to test the effectiveness of their designed training while there was no objective analysis of drivers' performance. There was no study which comprehensively tested different aspects such as trust, situational awareness, and drivers' performance for a designed training program. Some of them were successful to train drivers regarding one support feature but could not improve their knowledge regarding another feature.

The objective of the current experiment is designing and testing a training program to improve drivers' situation awareness when a DSF reaches the limits of its ODD, which eventually help drivers to take back control more sooner and efficiently when it required. To achieve this, a PC-based training program has been designed (Design of the training will be discussed in section 4.1 of the current chapter). Participants were recruited and assigned to three training condition groups (PC-based Training , user manual training and placebo Training). Participants in all groups were presented with a brief explanation of the L2 vehicles. Participants in user manual group further received a document indicating user manual information. Participants in PC-based training went through the PC-based training session. Participants in placebo training group received a training regarding other automated features apart from ACC and Lane Centering System which were the focus of

PC-based training. All participants then drove through post-test scenarios on the driving simulator.

4.1. Training program development

Previous studies showed that as training methods become more interactive, the trainee gains more knowledge about the specific subject (Burke et al., 2006). In fact, interactive training methods were observed to be much more effective in enhancing the trainee's knowledge and skills when compared to non-interactive video-based training (Burke et al., 2006). Studies such as Romoser and Fisher (2009) have found that an interactive training method such as 3M method (3M - mistakes, mentoring, mastery) was more effective that passive methods (Romoser & Fisher, 2009). This training method often referred to as error training (Ivancic IV & Hesketh, 2000). Ivancic and Hesketh (2000) showed that error training resulted in significantly better analogical transfer of knowledge to driving tests that corresponded to the situations encountered in the training. Analogical transfer refers to the ability to use familiar problems to solve other similar problems (Reeves & Weisberg, 1994).

The 3M method has been used in several studies (Fisher et al, 2017; Romoser & Fisher, 2009; Zafian et al., 2016) where drivers were successfully trained for complex driving skills such as hazard anticipation, hazard mitigation and attention maintenance in manual (non-automated) driving context (Muttart, 2013; Pradhan et al, 2005). This training method consists of three modules. First module is 'mistake' where the trainee is put into an unfamiliar setting and is allowed to make errors. Second module is 'mentoring' where the trainee is provided with real-time feedback and also guided to avoid such errors in future instances. Third module is mastery where the trainee is the given the opportunity to correct their mistakes.

The current experiment aimed to use 3M approach to improve drivers performance in complex transfer of control situations in L2 vehicle which require the drivers to recall L2 system limitations, to predict the hazards and to mitigate the hazards (by taking back control as a step of mitigation). The 3M method has been used due to the proven effectiveness of this approach to train drivers for learning and transferring of knowledge to action regarding complex skills and scenarios. To better explain the application of 3M approach in context of training driving for L2 systems, we will explain each of the modules in the context of a take back control scenario.

1) Mistake: In the first attempt, the participant were instructed to click on the automation on/off button when they feel the need to take back control from the L2 system at a particular scenario.
2) Mentoring: If participants did not respond correctly, they would receive real-time feedback regarding their mistake and informed about the solution. They were then asked to try the same scenario again. If they got the answer correct on the first or second tries, they were told that they did a great job and moved directly to the mastery stage.
3) Mastery. Participants were asked once again to show that they have mastered the skill. Thus, they were asked to practice once again in a more complex situation.

The training was delivered through a PC-based training program. PC-based training programs are realistic and economical approaches and they can easily be distributed on electronic media or can be made available on the Internet (Fisher et al., 2002; Pradhan et al., 2005). Hence, it would be an appropriate media for delivering the training. To design the PC-based training program, we used Microsoft PowerPoint which is easily accessible and editable for future use. More details about training program will be discussed in the section 4.2.4.

Eight types of scenarios were considered in the training program. Among those, seven types were based on those situations where DSF reaches its ODD limit as mentioned in the user manuals of different L2 vehicle models (Cadillac, 2018; Tesla, 2019). Another type of scenarios considered was based on those situations where drivers do not need to take back control from the system. This type was included to the training to make sure that participants will be presented with different type of scenarios featuring both takeover and non-takeover situations. This will prevent them from sensing a particular pattern and thus rule out the bias. The eight types of scenarios are as follows:

1) Curve: The L2 system may not manage to keep itself in the lane in sharp curves
2) Intersection: L2 system cannot predict potential hazards at the intersections and also may not detect cross-traffic
3) Invisible lane: L2 system may not keep the car in lane when it reaches areas where lane marking disappear (merges) or not visible (roadway conditions)
4) Vulnerable road users (pedestrian, bikes): L2 system may not detect any object on the road except a moving car in front of the vehicle
5) Stationary objects on the road (stop car, fallen trees, construction zone): L2 system may not detect stationary non-vehicle objects and also may not detect stationary lead vehicle if it was not detected as moving.

6) Non-standard shaped vehicles (Oversized truck, tractors, etc) : L2 system may not detect vehicles with Non-standard shape

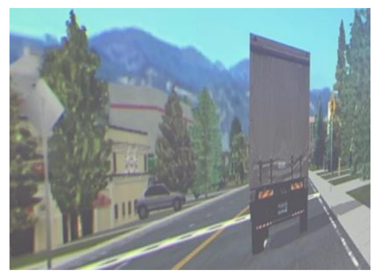
7) Unpredictable drivers (Distracted drivers, hidden drivers, etc) : L2 system may not work in the event of erratic behavior of another driver

8) No take-over (Control scenarios with no need to take back control from L2 system)

Considering the 8 type of scenarios above, 14 scenarios were used in our training. Seven of them were scenarios where participants needed to take back control and seven of them were scenarios where participants did need to take back control from the system (Table 8).

Table 8. Description of the scenarios for using in PC-based Training Program

No	Scenario type	Description	Image
1	Curve	The driver is traveling approaching a S-curved road section (one travel lane in either direction). At the end of the first curve (beginning of the second curve), a car is parked on right side of the curved road section.	
2	Intersection	The driver is approaching towards an uncontrolled intersection (two travel lanes in either direction). The adjacent traffic is controlled by a stop sign. Driver has the right of the way.	
3	Invisible lane	The driver approach the section of the road where the lane marking have been deteriorated	

4	Vulnerable road users	The driver is approaching a bike-trail. A bicyclist in the bike lane crossing the street	
5	Stationary objects on the road	The driver is travelling on a two-way road with two lanes in each side, when they encounter a construction zone	
6	Truck	The driver approaches an oversized vehicle moving at a slower speed than the speed limit. The oversized vehicle takes up an entire travel lane with its leftmost wheels protruding into the driver's travel lane.	
7	Distracted Driver	The drivers is travelling on a two-way road when they encounter a vehicle repeatedly swerving in and out of its lane.	
8-14	No take-over	Seven Control scenarios with no take back control events in different environmental settings (rural, urban, suburban)	

4.2. Method

In this experiment, first a PC- based training program was designed using 3M approach based on scenarios where DSF reaches its ODD limit and need drivers to take back control from the L2 system. Seven type of scenarios were considered in the training program. After which 36 participants were recruited and randomly assigned to one of the three training condition groups (User manual, Training and control). Participants in user manual training group received a document indicating user manual information. Participants in PC-based training group went through the training session. Participants in placebo training group received a training regarding other driver support features apart from ACC and Lane Centering System which were the focus of PC-based training. All participant then drove through post-test scenarios on driving simulator.

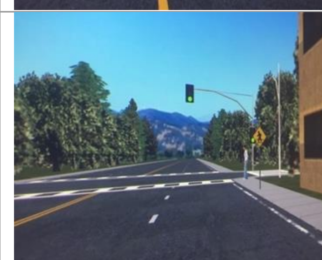
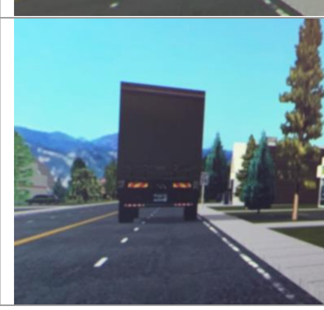
4.2.1. Participants

Thirty six participants were recruited from the University of Massachusetts Amherst campus and Amherst town using flyers and email advertisements. Only individuals with a valid United States driving license who did not wear eyeglasses were included in the study.

4.2.2. Scenarios

To test the effectiveness of the training program, 10 scenarios were designed (Table 9). All these scenarios were designed considering the 7 categories introduced in section 4.1. To design these scenarios ODD limitation of L2 systems mentioned in owners-manual of actual L2 vesicles were considered (Cadillac, 2018; Tesla, 2019). Scenario 1-3 are similar to the scenarios used in experiment 1.

Table 9. Post-drive Scenario Description for Experiment 2

No.	**Name**	**Description**	**Takeover required?**	**Image**
1	Merge	The driver reaches the end of a four-lane road (two travel lanes in either direction) which merges onto a two-lane road (one travel lane in either direction). There is a car following behind the driver into the merge.	Yes	
2	Curve	The driver is traveling along a curved road section, where a truck is parked on right side of the curved road section before a crosswalk. The truck is partly jutting onto the road obscuring a pedestrian.	Yes	
3	Intersection	The driver is approaching towards traffic signal-controlled intersection (two travel lanes in either direction) with a green light in the travel lane. A block of buildings obscures a pedestrian.	Yes	
4	Bike	The driver is driving on the right lane of a roadway and reaches a bicyclist riding on the extreme right side of the same lane	Yes	
5	Construction zone	The driver is travelling on a two-way road with two lanes in each side, when they encounter a construction zone	Yes	
6	Truck	The driver approaches an oversized vehicle moving at a slower speed than the speed limit. The oversized vehicle takes up an entire travel lane with its leftmost wheels protruding into the driver's travel lane.	Yes	

7	Car-cut	The driver approaches a driveway. A car cuts into the drivers pathway	Yes	
8	No takeover 1	This is a scenario in a suburban setting with no hazards	No	
9	No takeover 2	This is a scenario in a rural setting with no hazards	No	
10	No takeover 3	This is a scenario in an urban setting with no hazards	No	

4.2.3. Equipment

In terms of driving simulator and eye-tracker, the same equipment as experiment 1 was used in this experiment.

PC based training program was designed and presented using Microsoft PowerPoint. The program included 3 parts. In the first part of the training, participants were introduced to the training program and its interface, buttons and the task they would need to perform. They were instructed that they would receive several scenarios in the training and they would need to decide whether they should take back control from the system or not. In the second part, participants were presented with 14 scenarios (Table 8) where each scenario was presented by a sequence of snapshots (7 snapshots in total) from the drivers' point of view. Each snapshot lasted for 2 seconds. Seven of these scenarios included those situations where L2 system reached its ODD limit and the participants would need to take back control while the other seven would not require them to take back control. In cases where participants successfully took back control from the system on their first attempt, they were asked about the reasoning for their takeover action. If their response was incorrect, they were provided by the correct reason. If participants did not take back control for those scenarios where L2 system reached its ODD limits, participants received a message which guided them about their mistake and explained to them why it was necessary to take back control at that situation. Each participants had three attempts to gain mastery over each scenario. This was done to make sure that participants had enough chances to master their skills. Figure 20 shows the interface of the training program designed for this study.

Figure 20. PC-based training program interface

User manual training program included a text-based manuscript prepared based on the owner's manual of a real L2 system. In that manuscript, only those sections of the owner's manual related to the L2 systems and their limitations were included. After which, they received a multiple choice question test regarding the information presented in the manuscript. This was done to make sure they will read and pay attention to the material. The participants were informed that they will receive this test prior to them reading through the manuscript.

Placebo training program designed using Microsoft PowerPoint (Figure 21). This program included slides that informed the participants about the functionality and limitation of other driver support features apart from ACC and Lane Centering system. The features included in these slides were as follows: Automatic Parallel Parking, Automatic Reverse Braking, Anti-Lock Braking System, Drowsiness Alert, High Speed Alert, Back-up Camera, Parking Sensors, Temperature Warning, Hill Start Assist and Hill Descent Assist. The information provided for participants for these slides were adapted from mycardoeswhat.org. (My Car Does What, 2020). After which consistent with the other two training groups, they received a multiple choice question test regarding the same features.

Figure 21. Placebo training program

4.2.4. Experimental Design and Dependent variables and Hypotheses

The between-subjects independent variable in the experiment was the training program (PC-based training, user manual, placebo). The within-subjects independent variable in the experiment was the Post-drive scenario. The Post- drive scenarios (Table 8) were used to assess the effectiveness of the training program.

One dependent variable similar to phase III of first experiment, was drivers' takeover reaction, which was binary coded (Successful transfer of control as scored '1' and unsuccessful transfer of control was scored '0'). The second dependent variable was takeover time to hazard, the time interval at which drivers take back control up until the critical event. The third dependent variable was the overall SART score. The fourth dependent variable was participants' trust which was measured using trust questionnaire designed by Jian et al (2000). (Jian et al , 2000).

In this study, our first hypothesis was that the participants in the PC-based training group would take back control more successfully than drivers in user manual training group and placebo training group (H1). The second hypothesis was that the participants in the PC-based training group would take back control sooner than drivers in user manual training group and placebo training group (H2). The Third hypothesis was that the participants in the training group would have higher overall SART scores compared to the participants in user manual training group and placebo training group (H3). Our fourth hypothesis was that the participants' trust in automation would increase for those drivers in PC-based training group after receiving the training program compared to those in user manual training group or placebo training group (H4).

4.2.5. Procedure

After participants gave their consent, they were randomly assigned to either the control, user manual or PC based training groups. Participants were asked to fill out trust questionnaire. Participants in all groups were presented with a brief explanation of the L2 vehicles. Participants in user manual training group would further receive a document indicating user manual information regarding those limitations considered in the 10 scenarios mentioned in Table 8. Participants in PC-based training group went through the training session presented on Microsoft PowerPoint. Participants in placebo training group received the placebo training in the same platform as PC-based training group. All participants then drove through 10 designed scenarios on simulator. After each scenario they will be asked to fill the SART questionnaire. The procedure for the simulator drives were similar as the one explained in experiment 1. After driving through the scenarios participants will complete the trust questionnaire once again, and also fill out the demographics questionnaire and driver behavior questionnaire .

4.3. Results

For descriptive purposes drivers average age and average experience in each group (PC-based, user manual and placebo) was calculated. The average age of the drivers were 22.05 (SD = 1.68) for PC-based training, 22.92 (SD =3.28) years for User-manual group and 21.95 years (SD = 0.97) for Placebo group. To investigate if there was significant different between groups in terms of average age, ANOVA analysis was conducted. Results showed that there was no significant difference between groups (F = 0.706, P-value =0.5).

The average drivers' experience were 4.25 years (SD =2.203) for PC-based training group, 4.67 (SD =3.55) years for User-manual group and 4.79 years (SD = 0.65) for Placebo group. To investigate if there was significant different between groups in terms of average age, ANOVA analysis was conducted. Results showed that there was no significant difference between groups (F = 0.158, P-value =0.85).

The analysis of driver behavior questionnaire have been conducted based on a previous driving study (Reimer et al., 2005). ANOVA analysis showed that there was no significant difference in terms of Error (F=0.2350 , P-value =0.791) or Lapse (F= 0.2 , P-value = 0.819) or Violation (F=1.25, P-value = 0.299) between groups (PC-based, user manual and placebo).

4.3.1. Binary Takeover Responses

For descriptive purposes, the percentage of participants who took back control in each training group was calculated (Figure 22). In all scenarios, the percentage of successful take back control was highest in the PC-based training group compared to the User manual and Placebo training groups. In total, the percentage of participants who successfully took back control on time were higher for PC-based training group (91.71%) when compared to user manual group (27%) and placebo training group (23.71%). It should be noted that none of the participants took back control in the No-takeover scenarios, with the exception of one participant in the Placebo group who took back control for No-takeover 3 scenario.

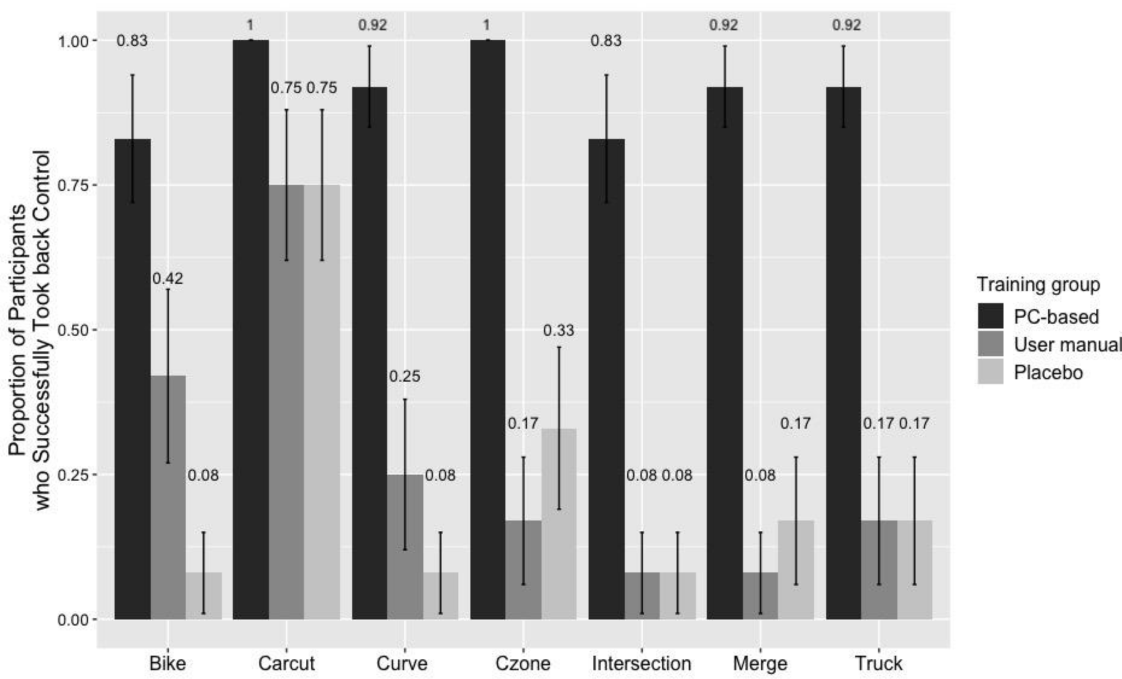


Figure 22. The percentage of participants who successfully took back control for each group

To determine whether the effect of dashboard was significant , a logistic regression model within GEE framework was used. Here, training group (PC-based , User manual , Placebo) was included as between subject factor, and takeover scenarios were included as within subject factor. Data analysis showed a significant main effect of training group (Wald Chi-Square = 25.732 , p-value < 0.001) and main effect of scenario (Wald Chi-Square = 33.287 , p-value < 0.001).

4.3.2. Takeover time to hazard

To further investigate take back control action of participants the time which elapsed between when drivers took back control and when the critical event was reached (takeover time to hazard) was calculated for each group (Figure 23). In all scenarios, participants in the PC-based training group took back control sooner compared to the user manual and placebo training groups. In average, participants in the PC-based training group took back control 7.05 seconds before the hazards (SD =1.17), participants in the user manual group took back control 1.93 seconds before the hazards (SD = 1.24) and participant in the placebo group took back control 1.83 seconds before the hazards (SD = 1.33).

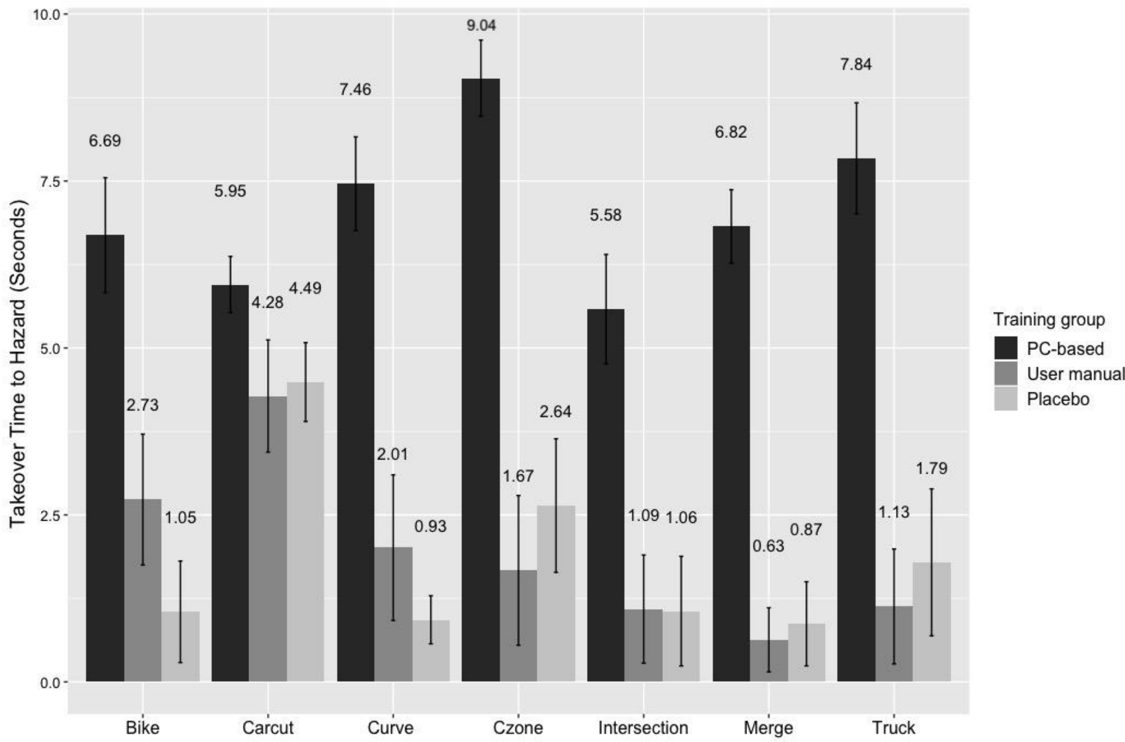


Figure 23 . Average Takeover Time to Hazard for each training groups

A 3 (training group) × 7 (scenario) factorial ANOVA was performed. The result showed that there was a significant main effect of training group ($F(2, 231) = 97.39$, p-value < 0.001). There was a significant main effect of scenarios ($F(6,231) = 3.27$, p-value < 0.01). To investigate which of the training programs were significantly different from each other, a Bonferroni post hoc analysis was performed, and results showed that there was a significant different between PC-based and user manual groups (p-value <0.001) and PC-based and Placebo groups (p-value<0.001) but no significant different between Placebo and User manual groups (P-value > 0.05).

4.3.3. Situational Awareness

Overall SART scores of participants were calculated for all training groups. The mean overall SART scores for each group for different scenarios are presented in Figure *24*. In all scenarios, participants in the PC-based training group had higher total SART score compared to the User manual and Placebo training groups. In total, the mean total SART score for participants in the PC-based training group was 22.03 (SD =1.41), for participants in the User manual was 15.20 (SD = 2.59) and for the participant in the Placebo was 10.84 (SD = 1.95).

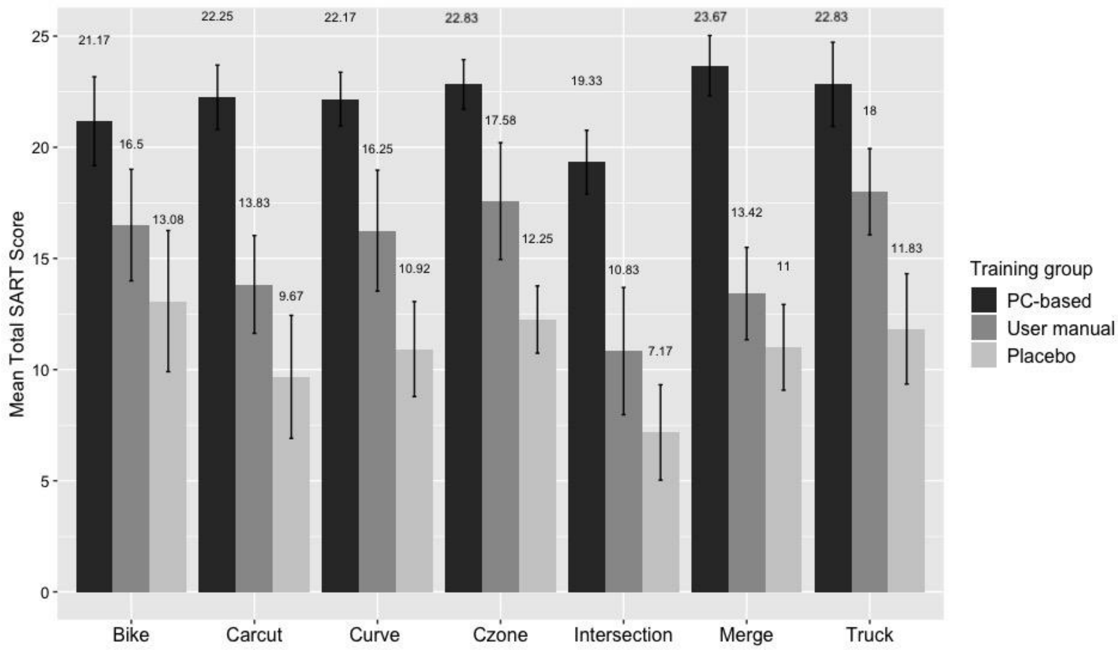


Figure 24. Mean overall SART scores for each training group

To determine if there was a significant difference between mean overall SART scores of participants between groups, A 3 (training group) × 7 (scenario) factorial ANOVA was performed. Results showed that there was a significant main effect of training ($F(2,231) = 48.20$, P-value<0.001). There was no significant effect of scenarios. Bonferroni post hoc analysis showed that there was a significant different between all the combination of the trainings (P-value <0.001).

4.3.4. Trust on Automation

As mentioned earlier, participants were asked to fill the trust questionnaire (Jian et al., 2000) once before the session and once after the session. Overall trust scores were calculated for each of the time and each group of training (PC-based, User manual, Placebo). The mean overall trust score for each group are presented in Figure 25.

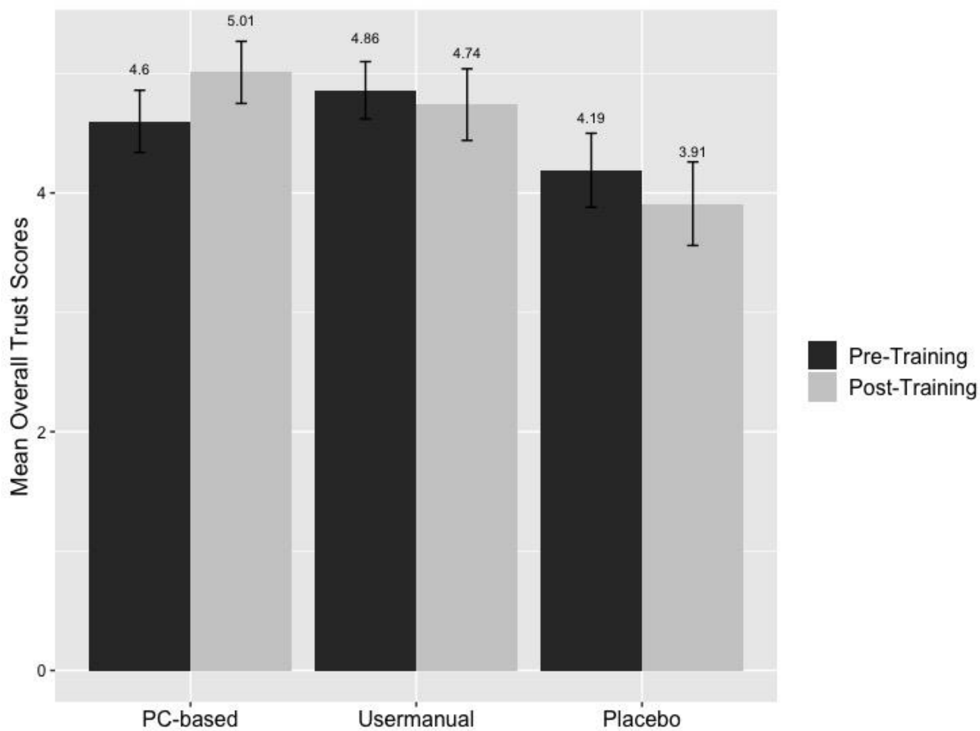


Figure 25. Mean overall trust scores for each training group

To investigate the difference of mean overall trust scores between groups, One-way ANOVA analysis was performed separately for pre-trust questionnaire and post-trust questionnaire. Results showed that there was no significant difference between participant mean overall trust scores for pre-trust questionnaires ($F(2,33) = 1.52$, P-value = 0.232). Results also showed that there was a significant effect of training program on participants scores for post-trust questionnaire ($F(2,33) = 3.51$, P-value = 0.041), Bonferroni post hoc analysis showed that participant in training group had higher post-trust score than participant in placebo group (P-value =0.048). There was no significant difference between participant in placebo and user manual group (P-value = 0.188).

4.3.5. Combined results from Experiment 1 and Experiment 2

Among all the scenarios considered for simulator testing, three scenarios (merge, curve, intersection) was common for both experiment. Takeover responses from both experiment for the mentioned three scenarios, show that the responses of participants were not that different for binary coded takeover data between two experiments (Advanced/Basic Dashboard vs PC-based training) as seen in Figure 25. Due to the difference of two experiments in terms of timing (The two experiment took place one year apart from each other), design of the experiments and presence of different scenarios and survey measures, the statistical analysis has not been conducted and we have to rely solely on descriptive information. As Figure 25 shows in most of the cases, participants in PC-based training group took back control as often as those in Advanced Dashboard group, despite the former group receiving no real time takeover feedback.

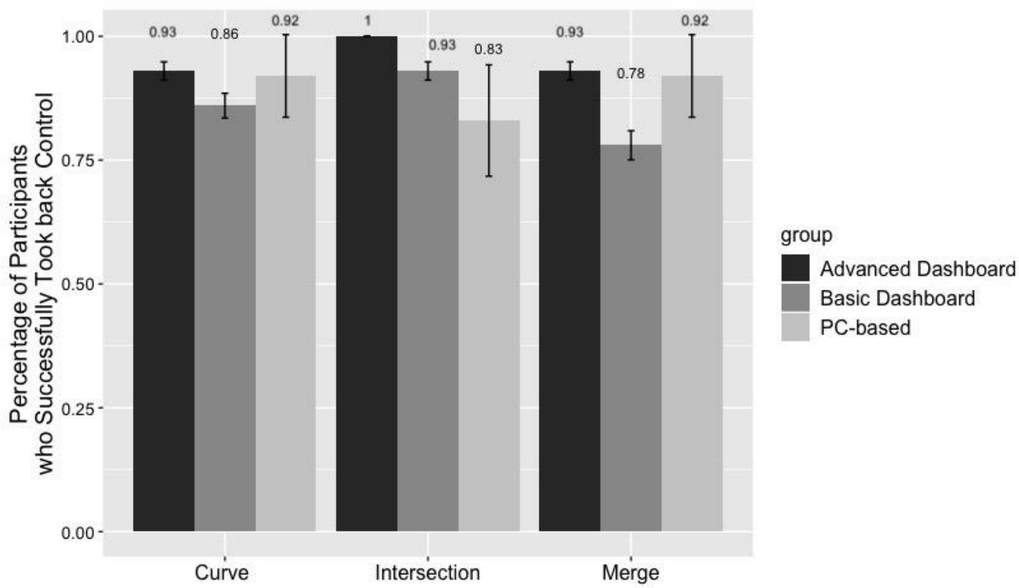


Figure 26. The percentage of participants who successfully took back control

Similar to descriptive information regarding binary coded takeover responses, the takeover time to hazards for all of the above mentioned groups were also integrated into Figure 26. Here we see that in most of the cases the PC-based training group took back control earlier than Advanced and Basic dashboard groups. Considering the above mentioned descriptive findings, one could argue that the PC-based training program was a good alternative method to improve drivers takeover responses for the mentioned scenarios. However, it also needs to be pointed out that the testing session for the training group took place immediately after the conclusion of training session. This may have caused the participants to better recall their newly acquired skills and knowledge compared to a real world situation where a person may not be able to recall and appropriately apply the skills for takeover situations. Whereas real-time feedback such as those seen in both Basic and Advanced dashboard would assist drivers to recognize and takeover control when needed.

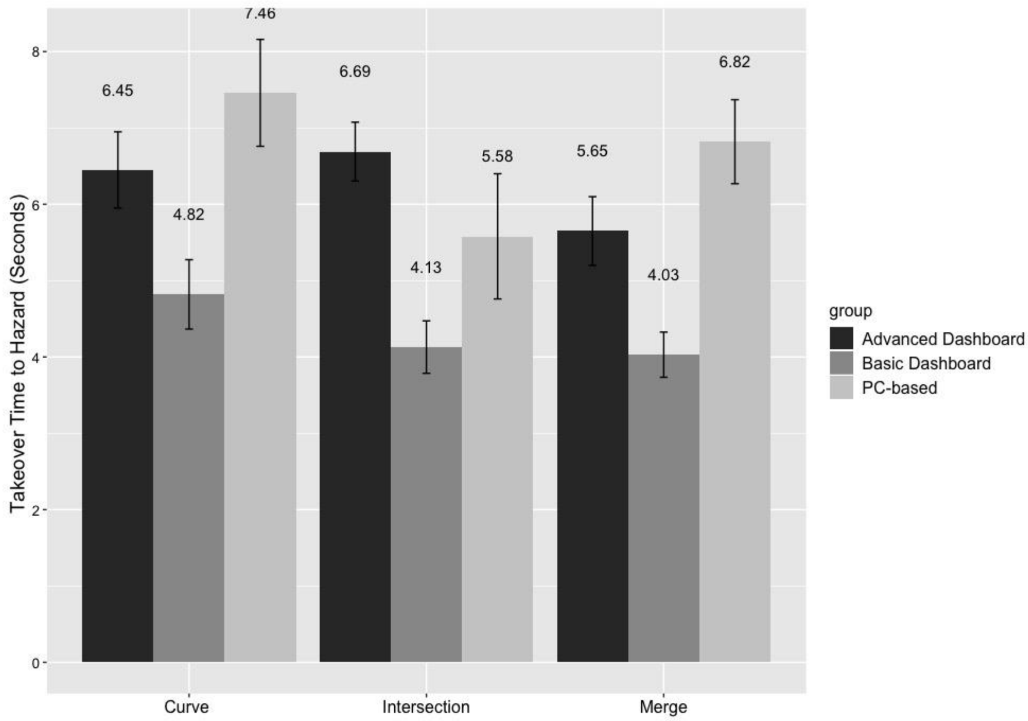


Figure 27. Average Takeover Time to Hazard

4.4 Conclusion

The objective of this experiment was to determine whether a PC-based training program using 3M approach could help drivers to take back control successfully when L2 system limitations are reached, improve their situational awareness as well as increase their trust in automation. Three different training program were conceptualized and designed for the purposes of this experiment : PC-based training program, user manual training program and placebo training program. In the PC-based training program, participants had an opportunity to practice, make mistake, learn and become master in taking back control situations where L2 systems reached it limitations. In the user manual training program, participants were provided with a text-based manuscript based on a real world owner's manual of an L2 system. Placebo training program was designed by including several other driver support feature rather than ACC and Lane Centering system which were the focus of our PC-based training program.

After completing their respective training programs, participants drove through ten scenarios on a fixed based driving simulator to test their response to different scenarios featuring both takeover and non-takeover situations during automated driving. Non-takeover scenarios were presented to the participants to make sure that did not develop a biased expectation to take back control for all the presented scenarios and to make sure their experience with L2 system was similar to real world situations where takeover situation may not be as prominent. Their takeover response was collected through the vehicle output of the driving simulator. To assess their situational awareness, and trust in automation, they were provided with SART (Selcon & Taylor, 1990) and Trust (Jian et al., 2000) questionnaires.

Results from the analysis of binary coded takeover responses showed that there was a main effect of training program on successful takeover control instances whenever the L2 system reached its limitations. PC-based training group took back control significantly more (91.71%) when compared to user manual training group (27%) and placebo training group (23.71%). This was consistent with our first hypothesis (H1). This may indicate that participants who received PC-based training recognized and took back control successfully when needed far more than their contour parts in other training groups. These results are consistent with past studies which showed that there user manuals were not sufficient to improve drivers knowledge regarding drivers support features (Boelhouwer et al., 2019; Jenness et al., 2008). Past studies also showed that many drivers do not read the user manuals completely (Leonard & Karnes, 2000). Considering the fact that the drivers in this study received only a specific section of the user manual and were given enough time to read through it before driving through post-test scenarios right after, one could argue that drivers in the real world may have gained/recalled less information from the user manuals. It should be noted that none of the participants in the training group did not take back control for No-takeover scenarios. This indicates that PC-based training did not cause people to be overly sensitive.

To further investigate the drivers takeover responses, takeover time to hazard was calculated for all the participants in each group. Results showed that participants in PC-based training group took back control sooner (7.05 seconds before the hazards) when compared to user manual training group (1.93 seconds) and placebo training group (1.83 seconds). This shows that not only PC-based training group took back control more successfully but also that they took back control significantly sooner than the other two groups. Post-hoc analysis showed that there was no significant difference of the takeover time to hazard between user manual and placebo training groups. This may indicate that user manual information regarding the L2 systems limitations may not be sufficient to educate drivers regarding those situations that they need to take back control from the system. This result was consistent with the finding from other studies which showed owner’s manual were not effective to improve the knowledge of the drivers regarding driver support feature (Boelhouwer et al., 2019; Jenness et al., 2008). These results were further strengthen our the results from binary coded takeover data and were consistent with our second hypothesis (H2).

In order to investigate the situational awareness of the participants during their post-test drives on the simulator, their overall SART scores derived from their responses on the

SART questionnaire were analyzed. The results indicated that participants in PC-based training group had significantly higher overall SART scores when compared to user manual and placebo training groups. As mentioned earlier, drivers in PC-based training group took back control more successfully that the other two groups. These results along with those from SART scores are consistent with past studies which have shown that drivers who had higher SART scores were more likely to successfully take back control from automated systems (Van Den Beukel & Van Der Voort, 2013). This could serve as another indicator about the effectiveness of the PC-based training program and is consistent with our third hypothesis (H3). No significant differences were observed between user manual and placebo training groups during the post hoc analysis. It should be worth pointing out that owner's manual were not at all sufficient to help drivers be situationally aware regarding the presented scenarios which featured some of the critical L2 system limitations.

To examine the effect of the training programs on participants trust in automation, the overall trust scores derived from participants responses on trust questionnaire before and after the sessions were analyzed. Results showed that there was no difference between participants trust before they received their respective training program. This showed that the participants did not have different level of trust in each group before their exposure to the training program and simulator scenarios, thereby ruling out any possible confounds in their subsequent performance. Analysis of post-trust questionnaire showed that participants in PC-based training group came out of the session with a higher degree of trust when compared to the user manual and placebo groups. This was consistent with the findings from a past study (Payre et al., 2016) which showed that an elaborative training improved the trust of the participants in automation. These results are also consistent with our third hypothesis (H3). One may point out the increase in trust levels may not necessarily be a good outcome of training, since it may cause drivers to over-rely on the system. However, considering the fact that the participants in PC-based training group performed significantly better with regards to their takeover responses and had the highest situational awareness among all the groups, we could assume that the training did not cause overreliance on the system but instead improved and calibrated their overall trust on the system.

The study has some limitations as noted here. First, the driving session of the study was conducted on a driving simulator and despite the high fidelity of the driving simulator, to analyze constructs such as situational awareness and trust, the external validity could be improved by conducting an on road study. Second, due to the fact that the current study incorporated a between-subject design, it could be argued that complete homogeneity was not maintained across the groups despite random assignment. However, the results from demographics questionnaire and driver behavior (DBQ) questionnaire showed that there was no significant different in terms of age and driving experience and DBQ ratings between participants of different group. We also did a prescreening procedures to make sure none of the participants had any prior information or experience with L2 systems in vehicles. This helped to minimize the confounds imposed by between subject design and yet benefit from this type of design by not having learning effect that would otherwise be caused by a within subject experimental design. Third, a larger sample size would be helpful to generalize the findings. Initial sample size considered for this experiment was larger but due to the onset of the COVID-19 pandemic, the sample size had to be reduced.

Fourth, the number of the takeover scenarios consider in this study were limited. Despite the effort to consider examples of all important types of takeover situation scenarios, there are many scenarios with difference in details, locations, road geometries, etc., which could not be included in this study due to the limited timing of each session. Modifying the PC-based training and testing it for more scenarios could further improve generalization of this study's results. Fifth, In this study, pre-test simulator drives were not included due to the time limitations for each session. Having baseline drives before exposing the participants to training could further show how a training program affected ones' response before and after receiving it. It should also be mentioned that content presented in this dissertation reflects the views of the author and further validation may be needed to generalize the findings.

This study adds to the literature regarding the effectiveness of training program to improve drivers interaction with L2 systems. As mentioned in Chapter 2, despite the important role of training programs, there have been only a few training programs regarding L2 systems designed and tested and most of them were not successful to improve drivers performance and knowledge of the system. Moreover most of these studies depended on self-reported questionnaire and lacked an objective analysis of the drivers' performance. This study showed that a PC-based training program using 3M approach could help drivers learn from their mistake in a safe and controlled environment using an interactive PC-based platform. The tests showed that they performed significantly better than drivers who only received information from owners' manual or those who were receiving placebo training. The results from this study can shed a light on new approaches to design training and user education methods with regards to vehicle automation which is much needed considering unfortunate accidents reported due to the drivers lack of situational awareness and knowledge regarding the limitations of these type of vehicles.

CHAPTER 5

OVERALL CONCLUSIONS AND FUTURE WORK

5.1. Overall Conclusions

The primary aim of this dissertation was to design and test methods to improve drivers' behavior when L2 systems reaches its ODD limitations. Towards this end, this dissertation comprised of two main research objectives: 1) Design and test in-vehicle interfaces to improve drivers performance in transfer of control situations while driving with L2 systems; and 2) Develop and test a training program for use in driver support features contexts, with a focus on training drivers to understand L2 system limitations and enable them to takeover control from the system when needed.

To achieve the first objective, a three-phase research experiment was carried out resulting in design of three in-vehicle dashboard interfaces (Advanced, Basic and Original Dashboards). The testing phase for the effectiveness of the interfaces showed that participants took back control much more successfully and had higher situational awareness when they were exposed to the Advanced dashboard compared to the Basic and Original dashboard. However, despite the effectiveness of the Advanced dashboard, there are no current vehicles with the similar dashboard interfaces. Moreover, there are many situations where the L2 systems cannot detect and inform the drivers regarding its ODD limitations and takeover situations and hence, no dashboard interface could be effective for such cases. For example L2 systems like Cadillac Super Cruise cannot detect pedestrians and hence are not able to inform drivers to take back control in those situations which may involve any hazards regarding pedestrians. One also can argue that real-time feedback could be distractive and counterproductive for those situations where they are needed repeatedly (e.g. intersections). All these reasons led to research to seek alternate approaches to improve driver situational awareness and takeover responses while driving with L2 systems.

In second experiment, a new PC-based training program was designed to help drivers gain knowledge regarding system limitations and takeover situations. This experiment included two other training programs which were tested in comparison to the newly designed PC-based training. One was based on an owner's manual and in the other one, participants received a placebo training which did not give them any information regarding the target L2 systems (combination of ACC and Lane Centering System), rather gave information about other driving features (e.g. Automatic Parallel Parking). The reasoning to include an owner's manual method was to compare the effectiveness of existing information material with our newly designed PC-based training program. The results from this experiment showed that the participants who received the training from PC-based program were not only able to successfully takeback control more often but they did so much sooner than the participants in the other two groups. To add to this, they also had higher situational awareness regarding the takeover situation featured in this study. Despite the increased knowledge of the L2 system's limitations, participants in PC-based training group did not lose their trust in automation system and in fact their trust seemingly increased as seen by their responses on the trust questionnaire.

This study was an effort to address some of the human factors challenges while driving with L2 systems. Challenges such as lack of knowledge of drivers regarding ODD limitations of automated vehicles (Jenness et al., 2008; Larsson, 2012), driver disengagement and out-of-the-loop phenomenon (Navarro et al, 2016) while driving with

L2 systems, decreased situational awareness (Hirose et al, 2015; Merat & Jamson, 2009), as well as drivers confusion regarding the transfer of control situations. The first experiment attempted to address driver disengagement and decreased situational awareness by providing visual and auditory alerts through newly designed dashboard interfaces for effective transfer of control in limited number of roadway situations where L2 systems reached it ODD limits. The results showed that drivers took back control more effectively and had more situational awareness while using the newly designed interfaces. The second experiment was an effort to address drivers' lack of knowledge and situational awareness regarding ODD limitations of existing L2 systems where the systems cannot provide feedback to the drivers for several roadway situations and the drivers may need to depend on their prior knowledge about the systems' limits. Past studies have indicated that the owner's manual, as an available source of this information for drivers, were not effective when it comes to improving their knowledge (Mehlenbacher et al, 2002). Hence, there has been an urge for finding alternative tools which can help drivers gain necessary information regarding these systems' limitations and safety-critical situations. Training programs have been suggested as potential solutions which may help improve drivers' interaction with automated systems (Beggiato et al., 2015; Forster et al., 2019; Koustanaï et al., 2012; Payre et al., 2016) , and therefore, the second experiment aimed to design and test a PC-based training program to achieve this. The results showed that drivers took back control more effectively and had more situational awareness after receiving the designed training program.

To sum up, both experiments featured in this dissertation present compelling arguments to utilize different methods to improve drivers situational awareness and takeover responses. Depending on the nature of the situation (e.g. whether the L2 systems can detect a certain hazard on the road or when real-time feedback are needed repeatedly) either one of the two methods presented in this dissertation or an intelligent combination of both could be helpful to improve the drivers safety while using L2 systems. For instance, for those scenarios where the system can detect a situation outside its ODD limits, real-time feedback on the dashboard may serve as a good option. For example, most of L2 systems may be able to detect merges on the road, and hence for this situation, providing a real time feedback has some advantages over training program which would require drivers to recall the information and react accordingly. However, one could argue that there is no way to provide any information on dashboard interfaces when the car itself cannot detect some of the hazards on the roadway. For example, L2 systems may not be able to detect the pedestrian on the road and hence, cannot provide any feedback to the drivers. In such cases, training would be a more suitable option to educate drivers regarding these specific system limitations. Another disadvantage of having feedback through dashboard interfaces maybe their effect on driver distraction. Having too many elements on the dashboard interface may results in drivers distraction (Brooks & Rakotonirainy, 2005; J. D. Lee, 2017). To find out the best balance between real-time feedback (e.g. alerts presented on dashboard interfaces) and training drivers, more research is needed to compare the effect of combinations of these two methods in a single experiment.

5.2. Practical Implications and Future Works

This dissertation contributed to human factors domain by addressing challenges related to L2 systems. The findings from this dissertation could have several practical implications in the real world. Concepts presented in this dissertation regarding the user-centered design of dashboards could help researchers pursue more complex designs and build up on the present research. This could indirectly impact the way automobile manufacturer designs dashboard in commercial vehicles with L2 systems. Manufacturers could employ some of the key elements featured on our dashboard designs such as road geometry, object on the road way, etc., to improve their current dashboard designs to improve drivers interaction with automation system.

Moreover, this study also sheds light on inherent problems regarding the information presented in the owners' manual specially those related to the limitations of these systems which is critical safety related information for new owners. Both researchers and manufacturers could understand the urgency of looking into new ways to effectively transfer knowledge to the drivers. Alternatively they could build upon our PC-based training program to design a comprehensive and advanced training program to deliver at dealerships, driving schools, etc.

This effort showed that 3M approach of training was efficient in transferring safety critical information to the drivers with regards the ODD limitations of L2 systems. Future research works could focus on delivering training using 3M approach in context of L2 systems for other important constructs such as hazard perception, attention maintenance, etc. They could also design and test this training program using more advanced platforms such as virtual reality and augmented reality or even deliver the training inside the vehicle.

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