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Rebuilding Driver Situation Awareness through the use of Augmented Reality

MASTER DISSERTATION

Rúben José Gouveia Rodrigues
MASTER IN INFORMATICS ENGINEERING

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Rúben José Gouveia Rodrigues
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SUPERVISOR
Filipe Quintal

CO-SUPERVISOR
Augusto Esteves

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To each and every one of you – Thank you.

Abstract

More and more automation is becoming available in cars with the objective of ultimately making the driver just another passenger in the vehicle. However, before getting to that point, which is still very much in the distant future, any automated driving system will need to coexist with the driver, handing back control when the automation can not handle a situation it faces. Yet, in some situations, the driver may not be fully ready to take back control of the vehicle, since one of the big benefits that automation in the car will bring is the possibility of undertaking more complex non-driving tasks when the automated system is driving the vehicle, which might cause a loss of situational awareness.

Safe driving requires significant situational awareness and a control that becomes almost subconscious to the driver when in said driving task, but if the driver is engaging in non-driving related tasks when the automation is active, he/she may lose the situational awareness needed to resume the driving task. It's with this in mind we propose two new designs of the takeover request (TOR), through the use of Augmented Reality (AR), to help the driver regain that situational awareness, without sacrificing the driver's recovery of the control of the vehicle. This way the driver can safely take back control, given a non-critical situation that the autonomous system can not handle.

Keywords

Automated Vehicles, Transfer of Control, Takeover, Augmented Reality, Situation Awareness

Resumo

Cada vez mais automação está disponível nos automóveis, com o objetivo distante de tornar o condutor simplesmente outro passageiro no veículo. No entanto, antes de chegar a esse ponto no futuro distante, qualquer sistema de condução autónomo terá de coexistir com o condutor, devolvendo controlo quando a automação não conseguir lidar com a situação que enfrenta. Contudo, em algumas situações o condutor poderá não estar completamente pronto para resumir controlo do veículo, visto que um dos grandes benefícios que a automação no carro trará é a possibilidade de fazer outras tarefas, não relacionadas com a condução, mais complexas enquanto o sistema autónomo conduz o veículo, e isto poderá provocar uma perda de compreensão da situação.

Uma condução segura requer uma boa compreensão da situação e um controlo do veículo que quase se torna subconsciente para o condutor quando este conduz, mas se o condutor fazer outras tarefas não relacionadas com a condução enquanto a automação está ativa, ele/ela poderá perder a consciência da situação necessária para resumir a tarefa de condução Tendo em conta estes pontos propômos dois novos desenhos do *takeover request* (TOR), com o uso de Realidade Aumentada (AR), para ajudar o condutor a recuperar essa consciência da situação sem sacrificar a recuperação do controlo do veículo por parte do condutor. Desta maneira o condutor poderá resumir controlo do veículo com segurança face a uma situação não-crítica que o sistema autónomo não consegue manobrar.

Palavras Chave

Veículos Autónomos, Transferência de controlo, *Takeover*, Realidade Aumentada, Consciência da Situação

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Acronyms

AI artificial intelligence

ARDITI Agência Regional para o Desenvolvimento da Investigação, Tecnologia e Inovação

AR augmented reality

AV autonomous vehicle

HMD head-mounted display

HUD heads-up display

IS industry standard

IVIS in-vehicle infotainment system

NASA-TLX NASA Task Load Index

NDRT non-driving related task

ODD operational design domain

OOTL out-of-the-loop

SA situation awareness

SAE	Society of Automobile Engineers
SART	Situation Awareness Rating Technique
TOR	takeover request
TOC	transfer of control
VR	virtual reality
WSD	windshield display

1

Introduction

Contents

Autonomous cars are coming. This is an area many auto manufacturers are interested in and developing automated systems, that can take over the driving task, or some parts of the driving task, from the driver, in order to give the driver more free time and increase safety in the roads [1, 2, 3]. Yet the driver is still expected to be able to take back control from the system when it faces its limit and can not manoeuvre the situation safely, because, due to the state of the technology as of July 2024, these automated systems can only drive in very specific conditions.

In the downtime when the system is driving the car, it's expected that the driver will engage in non-driving related tasks (NDRTs), like scrolling through social media on a smartphone, watching videos or simply enjoying the passing by landscapes. While beneficial for the user, periods of automated driving significantly affects the driver's situation awareness (SA) and may negatively affect his driving when he needs to take over for the automated system, so it's of upmost importance to grab the driver's attention as quickly as possible so he can start to build his situation awareness.

Safety in the roads should be the main concern with automated systems driving the vehicle and, most importantly to this work, how the driver interacts with it when he/she needs to regain control of the car, especially with the known effects the software currently in vehicles, in the form of In-Vehicle Infotainment Systems (IVISs), has on the driver [4]. Most previous work in this area focus on how long the driver needs to take back control of the car **safely** against emergency situations, like approaching road works or faded lane markings [5, 6]. While that is an important point, it's expected most types of takeovers won't be critical/urgent and few papers focus on non-critical takeovers [7].

Along with this, a lot of research has been conducted on the effects of the tasks the driver undertakes when the automation is on and the fact that the driver might interleave it with the driving task, with some finding that the driver might not use the extra time to reassess the situation, and thus regain SA, but to continue the NDRT [8, 9].

Even though understanding how much time in advance a takeover request (TOR) should be given to ensure a safe transfer of control is important, according to Michon [10] driving can be broken into 3 levels: strategic, tactical and control, with most papers focusing on the latter one. And White et al., in a 2019 study [11] focused on rebuilding the driver's SA, on the tactical level, instead of only guaranteeing safe control of the vehicle, with promising results.

It's with this in mind we propose a redesign of the warnings used to alert the driver, for non-urgent takeovers, taking into account where the driver's eye gaze is pointed at through the use of augmented reality. The main expectations with automated vehicles is for the vehicle to become another workspace or a place of leisure, while the vehicle drives itself [12]. So if the user is using a laptop, looking out a window or turned to a passenger and talking, a simple dashboard warning may not be enough to alert and/or give enough information to the driver for him to take over control. So we propose a system where warnings are localized and more informative: if the user is looking out the window a warning may be given to switch the drivers' attention to another display with more information about the request. With more localized warnings and information regarding the environment, information that's important in Michon's tactical level, we hypothesize that the driver will be able to reacquaint himself quicker with the situation, and be more aware of his surroundings and drive safer thanks to higher situational awareness.

1.1 Our Proposal

We believe augmented reality (AR) can be used to great effect in not only warning the driver, but also helping the driver navigate the current situation to rebuild situational awareness in order to ensure a safer transition of control back to the human driver from the automated system.

With this in mind we propose two new systems, developed by the authors, to hopefully better help the driver in non-critical takeover situations: in the first system the takeover request (TOR) will make use of the heads-up display (HUD), something becoming more common in cars nowadays, with more detailed information in the center console; in the second system, AR will be used to provide the warning but also to provide contextual information to the driver about the situation around him, for example, the exit he needs to take or how close the car in the adjacent lane is.

We will compare these two novel approaches, designed by us, with the industry standard (IS) way to alert a driver to a takeover situation: an image flashing on the dashboard, along with an audio chime, with GPS information in the center console, inspired by Apple CarPlay and Android Auto. We'll conduct a study where participants test each of these three systems in order to either confirm or disprove the following hypotheses:

Hypothesis 1: The two proposed systems will lead to more assured transitions compared to the IS way.

Hypothesis 2: The two proposed systems will not decrease takeover quality compared to the IS way.

Hypothesis 3: The two proposed systems will result in lower mental workload ratings by the users than the IS way.

Hypothesis 4: The two proposed systems will result in higher situation awareness than the IS way.

Hypothesis 5: The AR system will result in higher takeover quality compared to the HUD warning with detailed information on the console system.

In the next section we will explore previous research and related work, starting with the driving task, software in the car and, most importantly, automation in the car, what the driver does when it's active, its effects on the driver and other findings regarding the takeover. Next we'll explain our implementation of the systems and the simulation used in the study to prove our hypothesis. Finally, we'll discuss the results found from our study and how it might impact TOR systems design.

2

Related Work

Contents

In this section we will start by defining the driving task, key to this work, then the effects of IVISs on the driver and the state of automated vehicles as of July 2024. Finally, we'll look at previous findings regarding automation in the vehicle: its effects on the driver, what the driver does when it's active and how the design of TOR systems can help, or not, when regaining control of the vehicle.

2.1 Driving Task

Even though automation in vehicles is a relatively new concept, driving isn't. Nonetheless, the understanding of what goes into the driving task and, especially, how this can be influenced by software is not fully known and the subject of much research in the early days of vehicles.

Back in 1985 John A. Michon proposed that the driving task could be seen in a hierarchical fashion and divided it in 3 levels, and 30 years later papers in this area still cite it as a valid breakdown of the driving task, and we believe it so to [13, 14, 11]. The three levels Michon proposed are explained below, based on the articles cited above:

- **Strategical level**: the drivers orientate themselves in order to make long term general plans and future projections, like, for example, the next steps to take to complete the intended route;
- **Tactical level**: the drivers perceive environmental cues, comprehend these and judge the current situation and might perform a limited amount of projection, just the next few seconds, in order to decide which possible actions to take or possible maneuvers to undertake, for example, coast to reduce headway to a car or brake to maintain it;
- **Control level**: this level encapsulates tasks such as lane keeping and speed regulation and, at a certain point, these become subconscious actions for the driver due to experience and constant application; hazard evaluation and some projection of lane position for the driver's vehicle and others on the road can also be considered in this level.

Michon's hierarchical structure of driving shows the importance of anticipation in driving in a safely manner, since the anticipation needed to build long term plans for the strategic level then influences the

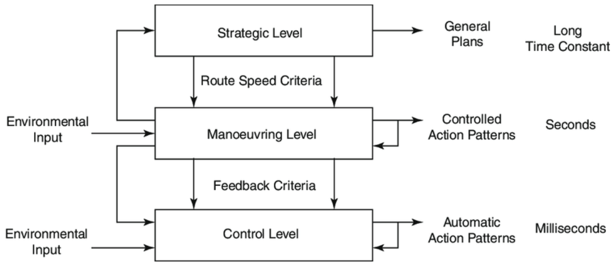


Figure 2.1: Michon's Driving Hierarchy [10].

possible actions to take in the tactical/manoeuvring level which then influences the actions the driver needs to perform in the control level, as can be seen in figure 2.1. And anticipation is particularly important in the tactical level of the hierarchy since it can allow the driver to react in an appropriate manner to other driver's movements and/or other situations on the road [14].

Most articles investigating the effects of automation in vehicles, in particular the period of manual driving following a takeover from the automated system, focus on assuring the driver regains safe control of the vehicle, i.e., the driver regains a control level similar to the control level that has become subconscious for some drivers according to Michon. While the control level in the hierarchy is the level most important to the immediate safety of the driver, the other 2 levels, in particular the tactical level, is just as important since if the driver isn't fully aware of his surroundings, if he isn't **situationally aware**, he may undertake unpredictable actions, actions not safe for him and/or the other drivers.

Situation awareness, according to [15], is defined as ”the perception of the elements in the environment within a volume of time and space and comprehension of their meaning and the projection of their status in the near future” and given the fact Endsley was trying to find a definition of situation awareness for dynamic systems and a car in movement could be seen as a dynamic system, we believe this definition can be applied to the automotive context and thus, is what we will refer to when we mention situation awareness. In terms of Michon's hierarchy, we believe situation awareness would fall in the tactical level, and be a key part of it, so it's as important to guarantee the driver has sufficient situational awareness as it is to guarantee he can control the vehicle; in other words, when taking back manual control of the vehicle, we believe the **tactical level is just as important as the control level**.

2.2 Distractions during driving

The rise in presence of IVISs presented the problem of having software in vehicle in terms of distracting the driver, an especially important problem given the fact it has been proven that the cause of a lot of crashes and near-crashes is driver inattention. At first these systems were only used to improve the driver's experience while driving the car, and to reduce manufacturing costs for automobile manufacturers. It allowed drivers to use navigation apps, choose what music to hear more easily and control other functions like seat warmers and mirrors.

However, it's pretty well documented that IVISs severely affect driver's attention since most of these systems force the driver's to take their eyes off the road [16, 4, 17]. And in terms of executing secondary tasks while driving it has been found drivers engaged in complex secondary tasks increased their risk of crashing by three times and moderate secondary tasks increased risk by two times compared to driving without such type of distraction [18].

To combat this issue, a lot of other possible forms of interaction were designed for the car, with the objective of reducing driver inattention and the time the driver spent without his eyes on the road. Research has found that the industry standard way, of a center console that the driver interacts with through touch, can be detrimental to safe driving since they demand substantive visual and cognitive load, which can have serious safety implications in terms of hampering the driver's steering capability, hazard detection, among other things [19].

A report evaluating the effects on the drivers of Apple CarPlay, Android Auto and other original equipment from the auto manufacturers systems found severe consequences of using these systems while driving. A report from 2018 found higher demand, both visual and cognitive, especially for native systems, however, even though Apple's and Android's systems worked better and showed less demands than native systems, they still showed somewhat high levels of demand [4].

A TRL report found the use of Apple's and Android's systems also influenced negatively the driver's capacity to control the vehicle laterally in the lane, to keep a consistent speed and to keep headway to the vehicle in front, while also forcing the driver's eyes off the road for longer than the recommended, so it was clear that interacting with these systems deteriorated driving performance, although the effects were less when the driver didn't need to take the eyes of the road [17].

As said before, other forms of interaction were researched. Di Campli San Vito investigated the effects of thermal feedback as an alternative to visual display of information, particularly for conveying navigation tips, but found users found it complex and thus not really feasible [20, 21, 22, 23, 24, 25]. Several authors investigated the effects of vibrotactile haptic feedback and found it augmented the use of visual interfaces, like the center consoles used for IVIS, and users preferred interactions when it was present (it made them more confident) but it did not improve driving performance significantly in most papers [25, 26, 27].

And some authors even investigated the use of the drivers' gaze (where the driver looks and how long for) to execute actions with an IVIS, a bit counter intuitive since taking the eyes off the road is what should be avoided to ensure safe driving and indeed no real benefit was found in these studies, response times were longer than recommended and no real benefit to driving performance was found, even though there was the theoretical positive of keeping the hands on the wheel, with preference of users also not favouring a gaze approach [28, 29].

What the research above shows is that distractions in the car are detrimental to safe driving, a distracted driver faces a much higher chance of being involved in a crash or near-crash and executing tasks while driving is detrimental to driving performance. However, when automation becomes present in cars and drivers can become passengers for some portions of the journey, the driver performance may be hindered in the immediate moments after the driver takes over control from the automated system due to the out-of-the-loop problem, discussed further in the next section. So we believe it's imperative to guarantee that the user does not engage in any distracting tasks immediately after he takes control and is not completely in the loop again to ensure safe driving following a takeover.

2.3 Automated Vehicles

The distracting effects of IVIS could translate to when vehicles start becoming more automated since it's expected that drivers will use the time the car drives itself for other activities like work, leisure (for example watching videos or scrolling through social media) or even just enjoying the passing landscapes. If the driver is distracted he may lose awareness of the environment around him, something quite dangerous when it comes to driving.

Most predictions concerning the level and/or number of autonomous vehicles (AVs) on the road are overly ambitious [30], so it is fair to say partially automated vehicles will be around for the foreseeable future. Petermeijer et al. [31] found that the expectation is that full driving automation should not be accomplished for **10 years or more**, so drivers will share the driving task with the automated system for at least a part of the trip so they believe cooperation is necessary and important for safe transfers of control. And in these vehicles the driver will have to resume driving from the automated system when the vehicle meets the end of its **Operational design domain (ODD)** and, as such, needs to be aware of the surroundings to control the car safely.

In order to better clarify automation in the vehicle, and the different possible types of automation, the Society of Automobile Engineers (SAE) defined **6 levels of automation** in the vehicle, seen in figure in figure 2.2, and this is the standard used industry wide. Below we present said 6 levels:

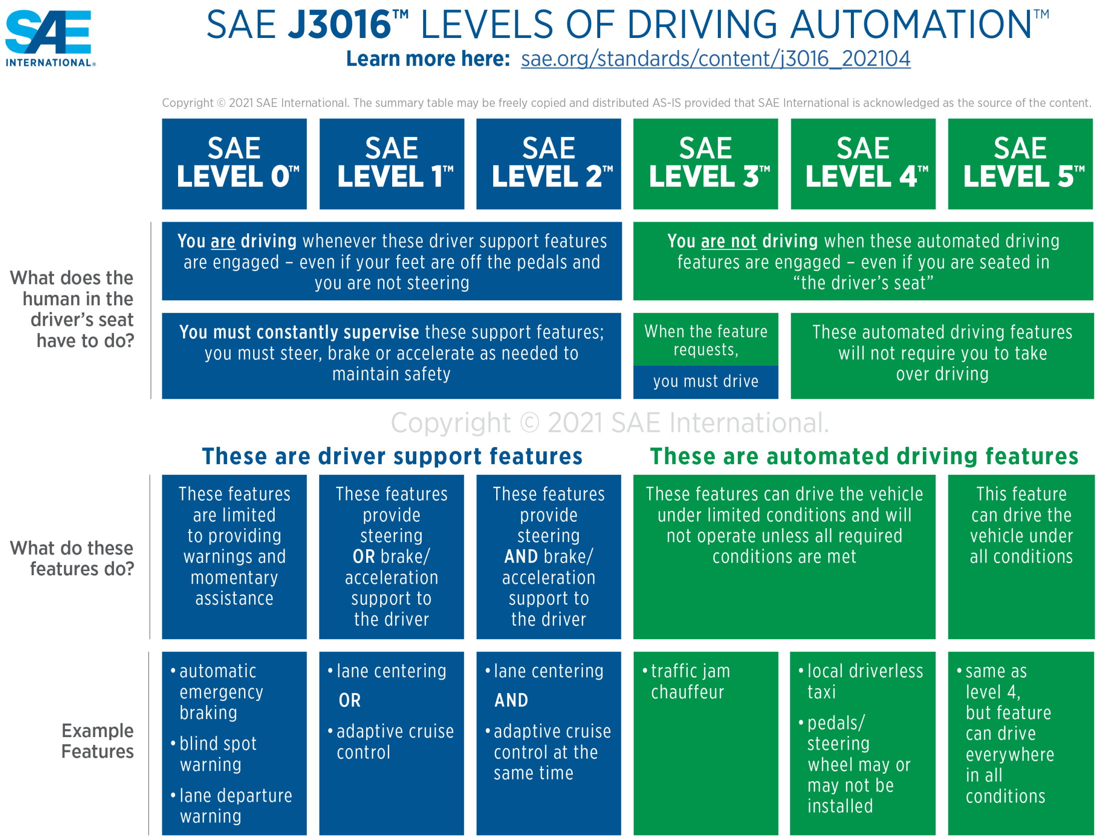
- **Level 0** - in this level the driver is driving manually and any software features only support him in the driving task, the features are limited to warnings and momentary assistance (for example blind spot warning or automatic emergency braking);

- **Level 1** - in this level the driver is driving manually and any software features either help in steering the car **or** help in braking/accelerating the car (for example lane centering **or** adaptive cruise control). The driver must constantly supervise these support features however and steer, brake or accelerate as needed to maintain safety;

- **Level 2** - in this level the driver is driving manually and any software features help in steering the car **and** help in braking/accelerating the car (in this level lane centering **and** adaptive cruise control can be used at the same time). The driver must constantly supervise these support features, just like in the previous level;

- **Level 3** - in this level, if the automated driving features are enabled, the driver is effectively not driving; yet, if the feature requests a transfer of control, then the driver must promptly resume driving. In this level any automated driving features can only drive the vehicle under limited conditions and won't operate unless such conditions are met (for example traffic jam chauffeur is a level 3 automated driving feature);

- **Level 4** - in this level the automated driving features don't require supervision or for the driver to take control and, as such, the driver isn't driving when the features are enabled. However, the automated driving features can only drive the car under certain conditions, outside of these conditions, the driver needs to drive the vehicle manually. A local driverless taxi is an example of a level 4 vehicle, if it needs to go into the highway a driver would be needed to manually control the vehicle;
- **Level 5** - the highest level of automation, the driver doesn't need to supervise or take over driving, in this level the automated driving features can drive the vehicle under all conditions. This is the only level where a driver is not needed and becomes another passenger;



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	SAE LEVEL 0™	SAE LEVEL 1™	SAE LEVEL 2™	SAE LEVEL 3™	SAE LEVEL 4™	SAE LEVEL 5™
What does the human in the driver's seat have to do?	**You are driving** whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			**You are not driving** when these automated driving features are engaged – even if you are seated in "the driver's seat"		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	
	These are driver support features			**These are automated driving features**		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering **OR** brake/ acceleration support to the driver	These features provide steering **AND** brake/ acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering **OR** • adaptive cruise control	• lane centering **AND** • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/ steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

Figure 2.2: Six levels of automation as proposed by the SAE [32].

Currently, more and more vehicles are equipped with level 2 automated driving features, more present in the higher end vehicles at the moment. But with the expectation that it may become feasible to incorporate these into the more affordable automobiles. While these features are still reserved for the more expensive models, there is already some market share for cars with level 2 features, with an average of 20% share across the world, fluctuating between continents, with approximately 3.5 million new cars on the road with level 2 automated driving features by the end of 2020 and constantly growing year on year, with an increase of 78% compared to the end of 2019 [33].

Some auto manufacturers are already focusing considerable research and development (R&D) into level 3 automated driving systems, with some key brands like Mercedes, KIA, Hyundai, Honda and Audi all developing, and some already testing on the road, their own systems (while Tesla advertises a Full Self Driving program in some of their cars, this system is still considered level 2, as of 2022, according to the SAE guidelines) [34, 3, 2, 1].

Yet, regulations still stand in the way of a more rapid development and deployment of level 3 automated vehicles. The European Union is still catching up with the technology and have only just recently, as of 2022, made level 2 features mandatory for some vehicles and announced they would look to establish regulations both for level 3 and 4 vehicles in the future, recognizing the benefit of automated systems in vehicles in terms of safety [35]. The UN also extended the automated driving speed limit, in June of 2022, from 60 kilometers per hour (km/h) to 130 km/h and allowed automated lane changes, among other things, marking an increased belief in automated vehicles. Even though the UN still limits the use of such automated systems, it can only be enabled in roads where pedestrians and cyclists are prohibited and where opposing traffic is separated physically, it's clear belief in these automated systems is growing while still maintaining safety as the main concern, also evident from the requirements that must be met by auto makers to sell such vehicles such as technical requirements, audits, reporting and testing [36].

Our research clearly shows steps are being taken by governments and regulators to allow self-driving cars in some situations, which should help accelerate their development. However, if we're to regularly see self-driving cars take the commute away from drivers, even more steps need to be taken to expand the possible use of these automated systems.

2.4 Out-of-the-Loop problem in automated vehicles

Automation in vehicles will bring sizable benefits, like removing human error from driving (one of the main causes of accidents is human error), which would result in less accidents and road-related injuries and deaths; and more efficient driving, particularly in traffic conditions. Be that as it may, considerable disadvantages still stand in the way of more rapid development and implementation like the high costs of developing and implementing such systems and consequent high costs of such vehicles due to the expensive R&D, and questions of acceptance of such vehicles on the road by the general public [37, 38, 39].

As mentioned earlier, one of the main benefits automation in vehicles will bring to drivers is the extra available time given back to the driver while the automated system is in charge of the driving, time that can be used for leisure or work [40]. However this also poses one of the most important problems in this field, one that's already considered a disadvantage to AVs in the long term (forgetting driving skills), and that is the human **out-of-the-loop problem** [37].

The out-of-the-loop (OOTL) performance problem is defined as a loss of performance from a system operator as a consequence of automation in said system. This potential loss of skills and situation awareness, caused by problems and complacency while supervising the automation, might make operators unable to take back manual control of the system in case of system failure. Highly automated systems will only emphasize this problem more since automation will be available for longer periods of time, which will diminish the chances of the operator understanding the system and hinder possible manual performance even more [41]. Since the first mentions of the OOTL problem happened in the context of automation during flights, something commonplace now, it makes sense the OOTL problem is now an important topic with automation becoming more and more present in vehicles [41].

2.4.1 Non-driving related tasks and its effects during automated period

Several studies have investigated the severeness of the OOTL problem in the context of automated driving, how to reduce the performance losses that arise from it, and how the tasks the user undertakes while the automated system is active might influence the consequent period of manual driving.

Ebel et al. [42] found that varying levels of automation, as well as vehicle speed and road curvature, had significant differences in the driver's behaviour due to driver self-regulation. Driver self-regulation is a phenomenon that began to be studied when software entered the vehicle and the driver could undertake a NDRT while driving, but drivers didn't perform a NDRT whenever they wanted, they assessed the current situation and the driving demand expected and would try to only perform the NDRT when safe to do so and even adjust the driving behaviour to compensate for the extra workload. Previous studies have found that more automation in the vehicle will result in less driver engagement and, consequently, less capability of the driver to evaluate driving demand. The authors found that, with automation active, drivers interacted with the graphically more complex elements of the system more than without it active, possibly recognizing the risk that would put on driving demand; they also found that drivers extended the duration of the glances away from the road, beyond the recommended 2 seconds, with the automation active, even if the drivers were meant to be supervising said automation.

Detjen et al. [43] found that the constant presence of warnings during automated driving was counterproductive and distracting to the users, decreasing both NDRT performance and user experience and ultimately, users preferred warnings happen only during the takeover request (TOR). The authors also found that users didn't react well to warnings that adapted given their gaze position and eventually concluded that visual support during the TOR phase is helpful for drivers. And as mentioned before, Dejten et al., in 2020, [39] studied the effects of experience in the acceptance of automation, and found safety was the main acceptance factor, while finding the most popular NDRTs the users spent their time on while the automation was active: they found users **spent most their time looking out the window, with smartphone use coming in at a distant second**, possibly due to the low confidence in automation.

Wandtner et al. [44] evaluated the impact of different NDRTs on takeover performance after a period of highly automated driving, and found task modalities had a significant effect on several measures of takeover performance. Something possibly explained by the multiple resource theory which states that there will be a greater interference between two tasks that utilize common resources compared to two tasks that differ in several dimensions and, according to Wickens [45], two tasks that both demand similar levels of a given dimension will produce greater interference to one another than two tasks that demand separate levels. Previous research has also found evidence of a psychological phenomenon called task perseverance which is the tendency to complete a task once it has been initiated and potentially neglect more important goals, something dangerous in the automotive context since the driver might negate the important task of safe driving [46]. Since driving is predominantly a visual task, the results matched the expected according to the multiple resource theory, visual tasks were associated with longer response times but results also show that drivers self-regulate appropriately most of the time because drivers are aware of driving performance impairments due to the performance of NDRTs. In this study the authors also investigated the effects of a task lockout and found it had a significant advantage concerning hands-on time, but no other measures were affected. That being said, the authors concluded that a system initiated lockout of highly impairing tasks could be a promising approach to improve driving safety after a transfer of control.

Weaver and DeLucia [47] analysed various studies to discover which factors influence takeover performance during conditionally automated driving and found that engaging in NDRTs degraded takeover performance, especially if said tasks had overlapping resource demands. The authors only found weak evidence that shorter time budgets impaired takeover performance and no evidence that information support affected takeover performance, though to be noted that the information support studied by the authors related to information acquisition (the cause of the TOR), information analysis (indicate whether an adjacent lane is open), decision and action selection (recommend a specific action). The authors found a **speed-accuracy tradeoff in the takeover**, faster takeovers can only be achieved if takeover quality is sacrificed but with weak evidence to back it up, especially for time budgets of 10 or more seconds, like you would find for takeovers in non-critical situations. While engaging in NDRTs degraded takeover quality, it also made takeovers longer and a possible explanation for longer takeovers not leading to better takeover quality is the fact that the users probably didn't use the extra time to regain situation awareness but instead switch tasks. Yet, engaging in NDRTs might not be so bad since, according to malleable attentional resources theory, mental underload might lead to worse performance due to low task demands which might induce boredom in the user and complacency [48].

Dogan et al. [5], on the other hand, didn't find an effect of the type of NDRT, undertaken during the automation, on takeover quality, when comparing writing emails to watching videos. They also found drivers resorted to an immediate brake reaction when regaining control as a safety measure to stabilize the situation, a possibly dangerous behaviour, but one that might not occur if the driver regains the appropriate situational awareness. Wörle et al [49] studied the effects of sleeping on the transfer of control, drawing comparisons to aviation where, in long flights, pilots need to sleep; however, there is still a long time before automation allows this, or if it would even be allowed, and Wörle indeed found users would not sleep in the car if they could and rated taking over after sleep as unpleasant.

Naujoks et al. [50] also investigated driver's takeover performance after switching from different NDRTs while driving a SAE level 3 system, simulated by a Wizard of Oz vehicle, in non critical situations and found that tasks that required turning away from the road or holding an object increased takeover times and variance in the driver's lane position. After takeover, the authors only found statistically different values from manual driving conditions in the **first 5 seconds after takeover**, for the standard deviation of steering wheel angle and standard deviation of lane position. After these first 5 seconds the returned values are similar to manual driving. Even though the drivers were taking over control in non critical situations, they only used up to 5 seconds after the takeover request was emitted to take back manual control, so the results might be better if the drivers use more time to rebuild situational awareness, in non-critical situations.

Dogan et al. [14] investigated the effects of anticipatory information and NDRT involvement on the takeover and monitoring behaviour of the driver and found anticipatory information (in the form of traffic density and vehicle speed at the moment of the TOR) influenced the driver's monitoring behaviour but didn't impact takeover performance and found driver's needed a prolonged period to gain vehicle lateral control, regardless of anticipatory information or NDRT involvement. Authors found that NDRT involvement only extended the takeover time, without significant effects on the quality of the takeover and that drivers preferred **clear, observable information over subjective information**; and confirmed that the transfer of control is not instantaneous, so a small period of readjustment to regain lateral control of the vehicle is to be expected.

The literature shows the OOTL problem is a reality, since involvement in NDRT generally decreases takeover quality, especially when the NDRTs demanded more from the driver in terms of visual demands, which, with the increase of smartphone use and the possibility of working during the commute, would be the main demand from these NDRTs. In our opinion, this decrease in takeover quality could become smaller and smaller with driver experience in these types of situations, especially considering that limiting driver interaction with NDRT could prove to be counter-productive, according to malleable resource theory, as discussed previously.

2.4.2 Minimum time needed to takeover safely

Roberts et al. [6] found the **more information** the users had available to them during the TOR phase the **more comfortable they were taking back control** and, as such, took back control sooner with improvements both to driving performance as well as the consistency of the driver, from a L2 automated system; previous research has found that drivers who took back control with only 2 seconds to the hazards on the road could not maneuver them safely, drivers needed between 5 to 8 seconds to do so, so the more information and time given to drivers before the takeover the more comfortable they will be for the transfer of control (TOC).

Du et al. [51] investigated how the information given to the user can influence the takeover experience; in a previous study from them they investigated how information on the AVs actions can increase acceptance and found explaining why the vehicle is acting in a certain way and how the vehicle is acting, combined, increased acceptance. In this study they compared giving the 'why' information and the 'what will' information, i.e., the recommended future actions to negotiate the takeover, and found users preferred receiving both types of information, perceived it more useful, with event criticality influencing the perceived usefulness of the systems negatively; receiving just why there was a takeover request wasn't sufficient for the drivers in terms of ease of use and usefulness. Authors also compared an AR HUD to a combination of the AR HUD with speech and found the combination of the two was the preferred method of delivery, though AR HUDwas also found to be enough by itself, but speech by itself wasn't.

Pampel et al. [13] found that vehicle stabilization following a TOR can happen in just a few seconds in simple traffic environments, but **tactical level decisions benefit from longer times between the takeover request and the takeover itself**. When the driver is OOTL they enter a state of passive information processing and thus lose SA, so more time is required to rebuild the awareness of the system state and spatial awareness, both of the driver's own vehicle and those around him, to ensure a safe TOC. The authors found that a longer takeover time (of 50 seconds) improved tactical level behaviours, drivers increased their speed sooner which shows that longer takeover times can improve situational awareness and decision making on the tactical level. Whether drivers were playing a distracting game was not reflected in the speed variation measured, which might suggest playing the game didn't fully take drivers OOTL. In this study the authors forced the drivers to use the whole 50 seconds of the takeover time, which proved effective to regain SA, but Eriksson and Stanton found that driver-paced transitions lead to better lateral control. Overall, results of this study shows **longer takeover times help to achieve higher SA** and the authors found **worse lateral performance only in the first 10 seconds** of manual driving following the TOC.

White et al. [11], as mentioned in the introduction, is one of the few papers that focused first on rebuilding the driver's situational awareness rather than his control of the vehicle, opting to use a ”top-down” approach to guide the user, encouraging to check for hazards before regaining control and found that drivers that we're encouraged checked the mirrors significantly more than those who weren't and were simply told to takeover. Yet, while suggesting to check for hazards lead to more mirror checks, not all drivers did it, suggesting it may not be a fully effective method to rebuild SA. The authors also tested if receiving information during the period while automation was active was helpful and found that it didn't influence mirror checks but it lead to faster hands on wheel time compared to those who didn't receive system feedback but, again, found that neither measure helped immediate driving performance, possibly due to the drivers being physically OOTL rather than lacking situational awareness.

Capallera et al. [52] did a meta-analysis, (similar to Weaver and DeLucia but in 2022) of several studies and found that mental workload and SA decrease with increasing levels of automation, drivers' reaction time increased since the drivers need more time to perceive and understand the situation, and shorter warning times correspond to reduced recovery quality. The authors mentioned the three level model for situation awareness of Endsley [15], developed for the aviation field but we believe can be applied to the driving context, that consists of:

- **Level 1**: perception of elements in the environment;
- **Level 2**: comprehension of the current situation;
- **Level 3**: projection of future status.

Given this model, it's evident what information should be given to the user to rebuild situation awareness. The authors found that visual interactions were the most promising to support the drivers' SA and they point out that it could be useful if the information is focused, for example, show information in the HUD if the driver is looking at the windshield. Main recommendation they found is that, as mentioned before, NDRTs help with alertness and their absence might increase fatigue, so engaging in NDRTs while the automation is active might be necessary to help with the manual driving post-takeover.

Eriksson and Stanton published two key studies in this area, especially for takeovers in non-critical situations. In the first one [53] their main objective was to determine the amount of time it takes drivers to resume control from a highly automated vehicle in non-critical situations and found NDRTs increase the transition times. On the other hand, even though this is a widely cited and important contribution, it's become slightly outdated now since in their literature review the average lead time found was around six and a half seconds and it's expected that, with technology enhancements in the future, that takeover request will be emitted with more and more anticipation, something the authors pointed as a possibility. Their results show quite a wide time range to resume control, from 2 seconds up to almost 26 seconds, which shows drivers will use the time if it's available to them, but it's important they use the time to rebuild SA and not continue the NDRT.

In their second study [7] Eriksson and Stanton aimed to explore if the driver paced the transfer of control would counteract the after-effects of taking over found in most studies. They found that lane positioning was virtually unaffected when drivers took over in automated conditions (passive monitoring or secondary task involvement) compared to the manual baseline but the standard deviation of steering input was significantly greater in the automated conditions compared to the manual baseline. The authors point out that an increase in time between the TOR and the transfer of control extends the time horizon which should enable drivers to attain a higher tactical level compared to the critical transitions most found in literature, since, per Hollnagel, the ”essence of control is planning” which means a sudden transition likely has detrimental effects on driving performance without appropriate support. A reason pointed out by the authors, for the higher standard deviation of the steering wheel while lane positioning stayed comparable to the baseline, is that drivers were **recalibrating themselves to the driving task by exploring the vehicle dynamics** to check for changes; something that happens in most studies and may happen very frequently due to the lack of experience of the drivers with these systems. The lack of difference in lane positioning could be attributed to higher levels of control attained by the users thanks to the more time available and the self-pacing by the users.

Gold et al. in 2013 [54] found drivers could takeover with shorter takeover times but quality was generally worse, since the time needed to takeover should depend on how long the driver needs to gather information and develop sufficient situation awareness. Results showed that drivers tended to only look at the mirrors after getting their hands on the wheel, braked first before any steering input and the more time the drivers had available the less they used the brakes, possibly indicating safer, more predictable driving. However harsh, sudden braking maneuvers were more present in the takeover situations compared to the baseline drive, unnecessarily endangering following vehicles.

Lastly, Merat et al. [55] found that driver's ability to regain control of the vehicle, if they are OOTL due to the automation, is better if they're expecting the automation to be switched off (compared to being forced to takeover due to looking away from the road), something that might apply to non-critical situations.

The literature presented in this section shows that considerable research has been placed on determining how much time drivers need to avoid collisions when taking over in critical situations. Although they have produced positive results, with most studies indicating that as little as 10 seconds can be given to the driver for them to takeover and avoid emergency situations, they also show that the tactical level decisions suffer with lower takeover times and improve when drivers are given more time; which is what we expect to happen with the technological improvements expected: more time being available to the drivers as the systems can predict takeover situations with more and more anticipation.

2.4.3 The takeover phase

Since automated vehicles are becoming more and more of a reality and vehicle manufacturer's rush to develop them, more research is also being done on this topic. However, technology is not reliable enough right now, and probably won't be for several more years, to execute a drive from start to finish, so inevitably the driver will have to resume control. And a lot of research has been done on this important moment, the takeover phase, which includes the request and subsequent driver behavior; and we present important findings from previous studies below.

Nagaraju et al. [9] found evidences that the TOC does not take place in one step but rather it unfolds as a period of interleaving between the NDRT and the driving task, a process that is moderated by the time made available for the TOC so this interleaving is more likely to happen the more time is available. This study found support for an earlier study defining interleaving in the vehicle by Janssen [8] so it's to be expected that the user will interleave the NDRT with the driving task in a non-critical takeover situation with considerable time available for the transfer of control; the study found that with 15 seconds available users weren't as likely to interleave tasks as when 30 seconds were made available, however, from previous research, the drivers should be cautious and, correctly, not wait for a boundary in the NDRT to switch back to the driving task if such a delay would result in poorer driving performance, so some interleaving, that is to be expected, might not be very detrimental to the transfer of control.

Janssen et al. [8] proposed a framework of interleaving that may be observed if the driver is engaged in a NDRT and needs to takeover from the automated system and pointed out 3 important reasons why it's unrealistic to expect an immediate transfer of control:

- Research shows that in the early stages of the transfer the drivers might not immediately direct their attention to the driving task and **won't have sufficient awareness to act adequately**;
- Research shows that earlier tasks that are interrupted, as would be the case if the automated system reaches the end of its operational design domain, might impact negatively later tasks, like the manual driving task;
- No empirical evidence that drivers fully disengage from NDRTs when taking over control of the vehicle.

Detjen et al. [43] studied how adapting takeover requests according to the context of the NDRT the driver undertakes and if adapting them according to the driver's gaze could be beneficial. One of the few studies that used virtual reality (VR) like we did to run the experiment, the authors found a constant presence of visual warnings (highlighting potential hazards) during NDRT performance was deemed annoying and distracting and participants strongly favoured presenting warnings only during the TOR phase, users perceived as significantly more safer this way. And adapting the warnings according to the driver's eye gaze (turning them off when driver looks at the hazard) didn't help the driver's response to the takeover requests, the effect could be undesired for the driver.

Hong et al. [56] studied various methods of warning the driver for a TOR, over a four year long study, and found multimodal warnings are more effective than the single alternatives. They studied visual, auditory and haptic/vibration warning designs both for an unplanned (6 second lead time) and planned (15 seconds) takeover scenarios and found combining visual with auditory or haptic is the best option; speech message warnings were more suited to non urgent situations and the A-pillar LED light visual warning worked slightly better than the cluster/HUD visual warning in terms of reaction time.

When Morando et al. [57] studied driver-initiated Tesla Autopilot disengagements, with a considerable database, and found less than 5 percent of occasions the drivers checked their rear view mirror and only in around 10 % of occasions drivers checked their windows mirrors, both prior and after disengaging the automated systems.

Pakdamanian et al. [58] studied the effects of adapting advisory warnings according to the NDRT the driver undertook and found it had significant effects in making the driver's behavior when taking over: it improved driver situational awareness, demanded less attention and led to more positive user feedback compared to speech based warnings.

Large et al. [59] conducted a very rare longitudinal simulator study, participants didn't experience the automated driving only once, but rather through a period of 5 days. They found the lateral instability characteristic of driving immediately after taking over from an automated system diminished with time and also improved when participants were told to check for hazards. Just like other studies, the authors found mirror checks greatly improved when the driver was warned to do so versus when he wasn't told to do so and found that keeping drivers 'in-the-loop' during the automation (by presenting sensor state) had no impact on driver behaviour.

This short section highlights that car companies shouldn't expect the driver to immediately drop what their doing at the time of TOR, drivers will naturally interleave the NDRT undertaken with their preparation to regain control of the car, for some amount of time. As such, the research proves that systems should be designed with the user's expected behaviour in mind, especially in terms of the amount of time given to takeover to the driver; although it is also the driver's responsibility to use their time wisely and ensure they can takeover safely.

2.4.4 Takeover system design

With automation in the car increasing, research about how it should interact with the driver has increased significantly recently: how a takeover system should warn the user; the effects different ways of warning can have on the driver and his behaviour upon resuming driving; how warning modalities affect the driver; should automation explain its decisions to the driver, among many other topics, some of which we will address below.

Graefe et al. [60] studied how explainable artificial intelligence (AI) affected acceptability of a system that altered certain vehicle functions (temperature, routing, etc.) and found explanations did improve understandability of the system but insufficient explanations decreased acceptance. They found evidence that people spend little time looking at explanations which means that explanations should be concise and easy to understand. Participants assessed an informative and explainable system increased system transparency but led to lower satisfaction.

Some research has been done into AR in the vehicle, in particular windshield displays (WSDs). Ch et al. [61] pointed out that WSDs requires similar gaze angles as normal driving, looking at the road, so this technology could enhance driver situation and spatial awareness, and could also be used to improve the takeover process.

McDonald et al. [62] investigated how an AR HUD can improve the ”delivery” of warning signs and how it affects the driver's situation awareness and attention. They found presenting warning signs via an HUD may start the perception level of SA, level one, according to Endsley. They didn't find an effect on the driver's SA based on display type, but that's possibly due to the fact participants watched videos and didn't actually drive, not even in a simulator.

Riegler et al. [63] studied user preference about content delivery on an AR windshield display, with two different levels of automated system, a level 3 and a level 5 one, where the users could place windows anywhere they wanted on the windshield display. They found with a level 3 system participants favoured placing information directly above them, where a HUD typically is, while with a level 5 system they placed windows across a bigger area of the windshield. They found content type (warning, entertainment, etc.), age and gender of the participant had an influence on how they placed the windows and after a survey found around half of participants couldn't imagine themselves wearing AR glasses while driving, but as the technology gets better it's possible this opinion changes. This study provided a great basis for the design of our takeover system.

Häuslschmid et al. [64] pointed out that the top and bottom areas of the windshield are the best candidate areas for displaying information since it wouldn't obscure the driving scene, possibly helping the driver to regain SA in the case of our takeover system. Participants rated the WSDs positively and from their experiments the authors found a more distant image leads to better driving performance compared to a virtual image closer to the viewer, possibly because it allows the driver to accommodate faster to the demands of the driving scene and participants kept an acceptable driving performance when presented with information on the peripheral of their view.

Gabbard et al. in 2014 [65] wrote about the challenges and opportunities AR can bring to the automotive context. In 2014 a system to highlight other vehicles around the driver was already developed, using LIDAR, so we believe this could become a reality commercial in the future; and another study at the University of California found AR graphics reduced driver distraction and reaction time to speeding alerts. Mercedes developed an AR prototype that presented cues indicating upcoming turns to the driver, thus presenting navigation information at the right time and position, a promising idea.

Some of the challenges Gabbard and colleagues pointed out still don't get researched enough such as noise due to vibrations, but others such as tracking are a constant source of development. They stated monoscopic cues may be sufficient for automotive applications, especially since the traditional approach for delivering stereoscopic images (headsets, glasses) may not be suited for driving, though we believe with developments to AR glasses, like the Google glass, it may become acceptable in the future. How much AR could distract the driver is an important topic as well, with a study finding that a simple symbolic representation of a hidden vehicle may be enough for the driver to avoid it, as such, the driving scene should not be too cluttered with unnecessary information and the graphics should have some level of transparency to aid the driver in judging the driving scene. Although Gabbard and colleagues pointed out that glass/headsets to deliver AR may be unsuitable for driving technology develops fast, and 5 years later, in 2019 Wiegand and colleagues [66] pointed out that head-mounted displays (HMDs) are likely to shrink in form factor, pointing out that in an extreme case may become as small as contact lenses. Extreme case aside, in that 5 year span between the papers, a shrinkage in the form factor of VR/AR systems has already happened, so it's expected they will continue to shrink, and possibly become suitable for the driving task, enhancing the driving task.

The papers mentioned above were an important source when designing our innovative AR based system; it was based on these we made our choices pertaining to placement and design in order to best get the driver back up to speed and try and ensure a safer transfer of control.

The focus of this section was on the design of the takeover systems used to warn the drivers in the event of a TOR and how, and if, they affect takeover quality and the driver experience with them. The research above shows a wide variety of options have been studied, with advantages and disadvantages to each of them, but one of the main points that can be taken away from all of the options studied is that multimodal warnings are very important in order to alert the driver in the event of a TOR, with multimodal warnings ensuring that at least one of the senses of the driver is alerted to the need to takeover control of the vehicle and thus reducing the possibility of driver error in these situations.

2.4.5 Final state of the art considerations

As mentioned in the introduction, we can see in the related work that most studies in this area focus on critical situations and the minimum necessary time to ensure a safe TOC back to the driver. A lot of these studies also focus on the effects the NDRTs will have when the driver resumes control of the vehicle so we believe there is no need to investigate this question in our study.

As pointed out by Eriksson and Stanton, technology enhancements should allow for TORs to be emitted further and further in advance. It's with this in mind we opt to explore takeover situations in **non-critical situations**, with plenty of time available to the driver to takeover and the driver allowed to pace the transition as they see fit. And just like White et al. explored in their study, we will emphasize the **recovery of situational awareness** for the driver, something not really studied in takeover situations as we can see from the related work.

In order to raise situational awareness we'll test a medium not really explored by other studies, **AR**, in order to investigate if more contextual information and information related to the current state of the environment around the vehicle would be beneficial to the driver. Importantly though, we hope this won't come at a sacrifice to the driver's recovery of the physical control of the vehicle and the driver will still only need the, approximate, 5 to 10 seconds (as observed in previous work) to rediscover the vehicle dynamics and resume safe driving.

In the next section we will describe the systems we will implement and the study we plan to carry out in order to test said systems after their implementation.

3

Method

Contents

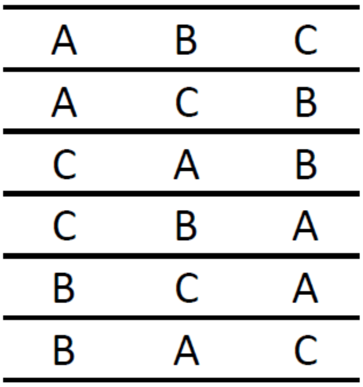
In order to study how a different approach to informing the user in the event of a takeover can affect said takeover and the period of manual driving that follows it we propose the development of 2 different systems, through the use of augmented reality (AR), to help rebuild the driver's situation awareness (SA) to, hopefully, ensure a **more safe and assured transfer of control (TOC)** from the automated system, like White found [11]. We wanted to explore the rebuilding of the driver's situational awareness since it's a key component of safe driving according to Michon and Dogan [10, 14]. In this section we explain, further in depth, the proposed systems we implemented and evaluate against the industry standard way of alerting the driver for a takeover (derived from our research of automated vehicles in the market as of 2022 [34, 1]) and explain our study proposal to evaluate said systems.

3.1 Participants

Participants in the study we're mainly researchers at Agência Regional para o Desenvolvimento da Investigação, Tecnologia e Inovação (ARDITI) who volunteered their time to participate in the study and were rewarded after their participation due to the length of the study. 14 persons opted to participate in the study but due to poor performance 2 of the participants we're excluded. Thus we present results from N=12 participants, enough participants to go around the Latin Square in figure 3.1 twice.

Of the 12 participants, 10 were men (83.33%) and 2 were women (16.67%). The age of the participants varied greatly, between 19 and 45 years old (Mean = 28.83; SD = 8.16 years of age). All participants had a driving license since that was an inclusion criteria; on average, participants had their driving license for 9 years (SD = 6.95 years). In terms of driving habits, 7 of the 12 participants said they have a daily commute, with the other 5 ranging from a couple times a week to very rarely, with one of them not having driven since getting their driver's license.

Participants rated their experience with each level of driving automation, as defined by the SAE, observable in figure 2.2, on a 5-point Likert scale, 1 being no experience and 5 being very experienced.



A	B	C
A	C	B
C	A	B
C	B	A
B	C	A
B	A	C

Figure 3.1: The Latin Square obtained with 3 conditions, in this case, 3 systems to test.

As expected no participant had any experience with a vehicle with level 3 or higher automated system, since these vehicles are very rare as of 2023. And experience with first 3 levels of automation decreased as the level increased, from an average of 2.25 for level 0 automation to 1.67 with level 1 automation and 1.42 with level 2 automation.

Participants also rated their cell phone use on a 5-point Likert scale, 1 being never and 5 being very often. Average phone use was very low at 1.75. Participants were also asked how many car accidents they were involved in, while driving: 7 of the participants were involved in a accident once, only one of the participants reported being involved in a few accidents while the rest of the participants we're never involved in one.

Finally, participants rated their experience with VR and AR on a 5-point Likert scale, 1 being no experience and 5 being very experienced. Participants had a bit of experience with VR (Mean = 2.33), less experience with AR (Mean = 1.83) and those that reported experience with VR did not report much motion sickness in previous experiences, on a 5-point Likert scale (Mean = 1.545).

3.2 Apparatus and Simulation

In this section we'll describe the equipment used, and why we opted to use it, along with the software used and designed in order to create the simulation environment used in the study and the NDRT we opted to have the user perform when the automation was active. We'll also explain how the participants experienced each of the three systems tested: the IS system, the HUD Warning system and the AR system.

3.2.1 Equipment

Although we're studying the impact of augmented reality (AR) on takeover systems, the current state of AR devices are not good enough, in our opinion, and as such, we used VR for the driving simulation and to simulate the AR aspect. Since we wanted to obtain data pertaining to where the participant was looking, particularly in the takeover moment, we needed a headset that allowed eye tracking, a technology that only few headsets support and allows us to record the location of the participant's gaze when needed. We opted for the HTC Vive Pro Eye, since it had the eye-tracking technology and the fact that it could be plugged into a computer so we could take advantage of computer hardware that could deliver better performance than running natively on the headset, using the headset's hardware, like the Pico Neo 2 Eye requires in order to use the eye-tracking technology the Pico headset offers, and with which we initially tested, before realizing performance was severely lacking on this headset.

To assure immersion, we opted for the driver to drive the vehicle in the simulation like they would in real life, with a wheel and pedals. For this, we opted for the set of Logitech G29 steering wheel and corresponding pedals. In order to simplify the driving, we opted for an automatic vehicle, i.e., the driver didn't need to perform gear shifts.

3.2.2 Driving Simulator

In order to simulate vehicles we used Traffic3D, an open-source traffic management solution available for Unity [67]. We found this solution to be good enough to simulate other vehicles on the road beside the one the participant would be driving. However, we found out Traffic3D was made with small scale simulations in mind, and as such, performance issues arose when using it with such a long map as ours. So changes were made to it to improve performance, with the main objective of reducing the reliance on lists and traversing them, since, due to Unity's poor support of multi-threading, all of the vehicle's processing was done on the main thread, along with the graphical operations, hence the poor performance. So, with the help of another Unity asset, we altered the vehicle steering so less list traversal was needed and the raycasts used to detect collisions were adapted to run in another thread, since raycasting is a very costly operation. With our optimizations the simulation became a lot smoother, hitting more than 60 frames per second with 40 AI cars loaded in. With the new way the AI cars operated, and since it was so performant, the same scripts were used to guide the participant's vehicle when he transferred control to the vehicle's automated system, to reduce the involvement of the person supervising the experiment.

Another technique common in game making was used, object pooling. Instead of creating vehicles at runtime, the original way Traffic3D was designed, a predefined number of vehicles were created at the beginning of the simulation and enabled when needed, being deactivated and returned to the pool of available vehicles when it reached the end of the path; thus removing object creation and deletion from the runtime of the simulation, costly operations in terms of performance.

3.2.3 Simulated Road and Takeover Situations

Not only is Traffic3D a traffic management solution, it also has a very useful feature to generate roads based on a real life map exported from OpenStreetMap. However, this feature has the limitation that OpenStreetMap has a limit on the amount of nodes that can be exported so we could only export stints of the highway one at a time. Nonetheless, we found a way of combining all the short maps exported from OpenStreetMap into one, combining the ends of each map together, to extend the amount of road possible to drive in the simulation. As such, in the simulation the participant could drive from Santa Cruz to Campanário using Madeira's Via Rápida, with some exits and entries to this roadway also loaded in.

One of the common situations a TOR might be issued is when the route involves taking a highway exit, since current automated systems only operate in highways, some can handle normal driving while some systems only function as 'traffic jam chauffeurs'. For our experiment, the automated system handled all the driving on the ’Via Rápida’ when enabled, controlling the longitudinal and lateral aspects of it; and reached the end of its operational design domain (ODD) upon nearing the exit on the planned route and thus, a TOR would be issued for the driver to regain control of the vehicle, 30 seconds before the ODD of the system. In order to ensure the driver would have to make a manoeuvre after regaining control, and not simply keep driving in the same lane, the automated system would take the vehicle to the left lane and as such, upon regaining control, the driver would have to switch from the left lane to the right lane to then take the exit, while looking out for cars in the right lane so as to not cause a collision, or switch lanes dangerously.

3.2.4 Non-Driving Related Tasks

In order to make development easier, and because it is an approximation of the most common behaviour expected of driver’s when automation is active (smartphone usage) the driver would watch a video on a mock tablet while automation was turned on. Ideally, we would have let the participant do what he/she/they wanted when the automation was on, like White et al. did in their study [11], but since the experiment took place in virtual reality this would mean taking the headset off and putting it on again, breaking the immersion and the unexpected feeling of a TOR.

Due to the fact the HTC Vive Pro Eye doesn’t support hand tracking, the participant, when the automation was active, needed to pickup a controller to engage with the tablet, but in order to facilitate this process and try to make it as seamless as possible the controller was placed next to the participant for the duration of the experiment.

3.2.5 Takeover Systems

We opted to test out 3 different takeover systems and compare the data obtained between these 3: one would be as close to the industry standard way as possible; in the second one a takeover warning would be issued in a HUD, a display projected in the windshield in front of the driver, slightly above the steering wheel, something becoming more common in vehicles, with information pertaining to the environment given to the user in the center console, something which might be done in automated vehicles since several studies show that users are more accepting of technology if given some explanation about the technology’s decision making; [51] and the third one a more experimental one: a solution in which augmented reality is used to convey information pertaining to the environment in its context, highlighting other vehicles, displaying route information in an appropriate location, etc. We will explore these systems further in depth below and show their appearance with the help of images.

Figure 3.2: The Industry Standard TOR.

3.2.5.A Industry Standard system

The most simple of the three systems, this system was based on the current observable takeover requests on vehicles with level 3 automated systems. We used a version of the image Tesla shows the driver to symbolize he/she/they needs to takeover, flashing it at the moment of the TOR, and replicated the GPS information the driver would have in this situation with an image displayed in a center console, indicating the route the driver needed to take after recovering control of the car. The TOR this system emitted can be observed in figure 3.2.

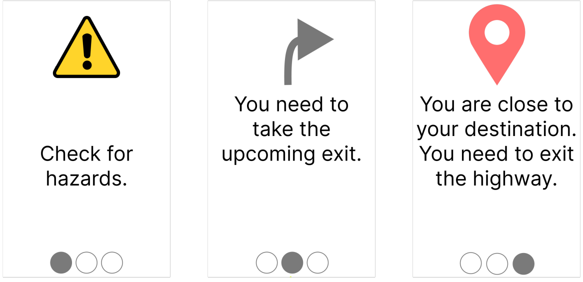
3.2.5.B HUD Warning system

The second system might become a possibility due to the fact that HUDs are becoming more prevalent in recent high-end vehicles. Since these displays started popping up in order to improve safety because they may reduce glances off the road, we believe they may be implemented in automated vehicles, especially during the early days of these systems where most systems are level 3 and the driver should be monitoring the driving, or may not be allowed to take up another task.

So, given that these displays may be implemented in automated vehicles, we designed a possible way a vehicle with a HUD and a center console would alert the driver in the event of a TOR. Using the same image used to alert the driver in the industry standard system, we designed a message that popped up on the HUD, flashing, with a short message alerting the driver.

To evaluate the possibility that short, objective messages about the situation would be beneficial to the driver when regaining situation awareness, something some papers indicate users prefer in these situations (objective information), we designed three panels that indicated the next actions the driver should take, observable in figure 3.4. [51, 11] When the TOR was emitted the message popped up on the HUD and center console displayed the middle panel in 3.4, the one indicating the driver needs to take the next exit. The driver could access the other panels by swiping right or left on the center console with the Vive Controller's touch pad circular button, both before regaining control and after regaining control. In figure 3.3 we can see what the driver would see when the TOR was emitted using this system.

Figure 3.3: The HUD Warning TOR, with the additional info in the center console.



Check for hazards.

You need to take the upcoming exit.

You are close to your destination. You need to exit the highway.

Figure 3.4: The three pieces of info that appeared in the center console in the HUD Warning TOR.

3.2.5.C Augmented Reality system

This last system is the most experimental one of the three but a worthy consideration considering more and more efforts are being done by companies to explore the AR space. In this system nothing is displayed on the center console; a overlay flashes up on the tablet, equal to the one that pops up on the HUD on the previous system; two overlays flash on the mirrors, one on the rear view and one on the right mirror (since the automated vehicle would be on the left lane) pointing out possible hazards around the vehicle and an outline of the nearest vehicle in the right lane appeared alongside the vehicle indicating how safe the manoeuvre was by the color of the outline, explained below:

- Green - manoeuvre is safe, nearest vehicle is far away;
- Yellow - manoeuvre is slightly risky, executing the manoeuvre would require the other vehicle to brake slightly to avoid the participant;
- Orange - manoeuvre is very risky, almost not safe, executing the manoeuvre would require the other vehicle to slam on the brakes to avoid a crash;
- Red - manoeuvre is not safe, executing it would cause a collision with the other vehicle.

Along with these warnings displayed around the cabin and in the proximity of the vehicle, observable in the figure 3.5, the signs pertaining to the exit the driver needed to take had overlays that shrunk

Figure 3.5: The AR system TOR around the driving cabin.

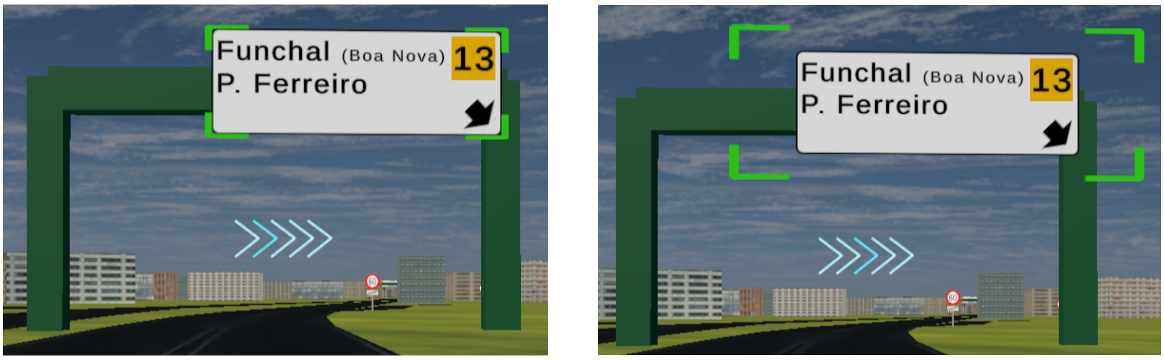


Figure 3.6: The AR system TOR on the signs and arrows signaling exit.

and expanded to capture the driver's attention, as you can see in figure 3.6. And finally, inspired in a Mercedes concept, arrows placed at the exit, flowing from left to right, indicated to the driver that he needed to exit the highway there, as you can see in figure 3.6. [68] When 15 seconds we're left to takeover the arrows flowed faster and the overlays on the signs moved faster as well.

For all of the systems, alongside the visual warnings, explained in the previous sections, an auditory warning was emitted as well. And 15 seconds before the ODD of the automated system the images that flash in each system flashed again, alongside the auditory warning being played again, but faster, symbolizing more urgency.

3.2.6 Data Collection

In order to understand how the systems explained before influenced the driver, both in his driving and behaviour, we tried to collect as much data as possible.

When it comes to the driving data, we opted to collect data for a minute, before the user turned the automated system on and after the user took over from the automated system. In this minute, every 0.02 seconds we collected:

- the input value of the accelerator and brake (value in the range of 0 to 1, 0 being no input and 1 being the maximum input);

- the absolute lane position of the vehicle, distance between center of the participant's vehicle and the center of the lane the participant is in, value varying between 0 (vehicle is at the center of the lane) and, approximately, 2.5 (vehicle is at the rightmost or leftmost point of the lane);
- the steering wheel angle, measured in degrees, varying between -450 (steering wheel is turned all the way to the left) and 450 (steering wheel is turned all the way to the right), with 0 being no steering input;
- the speed of the vehicle, measured in kilometers per hour.

For the eye gaze data, we used the position of the participant's eye to register when it entered and exited certain points of interest (ex. the mirrors and windows) and calculated how long each gaze lasted, along with how many times the participant gazed into each point.

Finally, to calculate the moment when each event happened (switch from left lane to right lane, switch from right lane to the exit) we examined the driver behaviour and then examined the data to pinpoint the exact moments each event happened.

3.3 Procedure

The first thing participants did was review and sign the informed consent, which contained a very short description of the objective of the study and the tasks that would be asked of the participants. After this, the participants filled out a quick survey to understand participants' demographic, driving experience, experience with vehicle automation and experience with VR and AR.

After this, we introduced the equipment and basic controls to the participants, and calibrated the eye-tracking technology of the headset to the participant's eyes. After the calibration we explained the structure of each experiment, how the participant would activate and deactivate the automation and why the automated system would alert the participant for the takeover, the fact that he needed to exit the highway. After this, we gave the participant some time to get to know the vehicle's dynamics and interact with the tablet, where he/she would watch a video while the automation was active.

When the participant was comfortable and maintaining an acceptable driving level, we introduced the first system they would test and gave him a short test for them to see how the system would alert them before the trial itself, so as they wouldn't need to learn it during the trial and produce unrealistic results. We did this short test for every system the participant tested. After performing the trial, the participant filled out the Situation Awareness Rating Technique (SART) questionnaire, the NASA Task Load Index (NASA-TLX) questionnaire and a short form where they evaluated the system.

In the table below we can observe the data we opted to collect and what changed between the experiments, i.e., the independent variables and the dependent variables of the study.

Independent variables	Dependent Variables
Driven path	Takeover quality
Time before TOR	Mean absolute lane position
System tested	Takeover time
	Driver eye gaze and behaviour

Table 3.1: Independent and dependent variables of the study.

After the participant did the trial for each of the three systems, we ended the experiment with a short interview with each participant to understand which system they preferred and their likes and dislikes with each one. We can observe a diagram of the study in the figure 3.7 below.

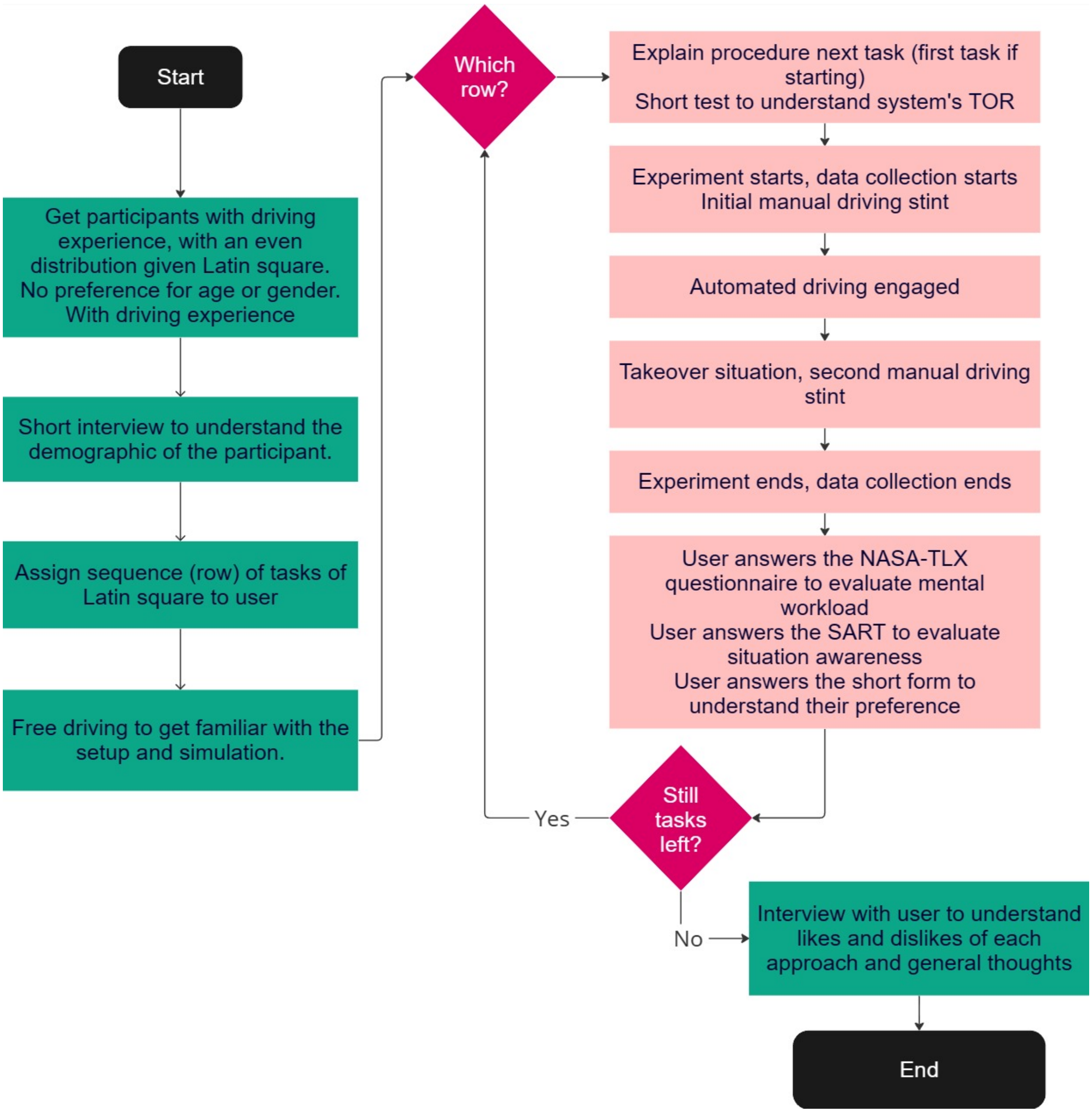


Figure 3.7: Diagram demonstrating the flow of the study procedure.

4

Results

Contents

In this chapter we will present the results obtained from the study performed to evaluate the possible differences between the three systems mentioned in the previous chapter, and if any statistical significant differences were found in any of the data we collected. First we'll start off with a comparison between the order of events and what time they happened when the driver was notified that they had to take over by the system's takeover request (TOR); then we'll present the driving data obtained after the participant took over, for each of the three systems, followed by a per system comparison with the baseline drive. Next we'll present the data of the gazes the participant made after the TOR was issued, to identify if any of the systems led to a change in behaviour of the participants and finally we'll finish with the data obtained from the answers the participants gave to each of the forms filled out after testing each of the systems. To be noted that when we mention "significant statistical difference" it's because the *p value* is lesser than or equal to 0.05 (*p value* ≤ 0.05).

4.1 Sequence of events

In this section we'll show how the participants reacted after the TOR was issued by presenting the average time certain important events happened after the TOR was issued:

- Hands on Wheel time: the average time for the participant to place both hands on the steering wheel;
- Takeover time: the average time for the participant to deactivate the automated system and regain manual control of the car;
- First Acceleration input: the average amount of time passed before the user pressed the accelerator for the first time;
- Left lane to Right lane switch: the average amount of time elapsed before the user made the switch from the left lane for the right lane;
- First Brake input: the average amount of time passed before the user pressed the brake for the first time;
- Right lane to Exit lane switch: the average amount of time elapsed before the user exited the highway, making the switch from the right lane to the exit lane.

As we can see from the figure 4.1, the HUD Warning system led to drivers taking a little more time to place both hands on the wheel, but it was not a significant statistical difference (*Q*: 1.29685, *p*: 0.28696), and the AR system increased the amount of time between placing both hands on the wheel and turning off the automated system, but not a significant difference in terms of takeover time

(*Q*: 0.96072, *p*: 0.39306). In terms of the time before the driver's first acceleration input, no significant statistical difference was found between the three systems (*Q*: 0.84551, *p*: 0.43843); but there was a larger difference between this and the average time to switch from the left lane to the right lane, with drivers taking longer to perform the switch when using the AR system than the other two systems, though there was no significant statistical difference for the time to make said switch (*Q*: 2.01181, *p*: 0.14982).

On the other hand, the difference between the aforementioned switch and the driver's first brake input is shorter for the AR system than the other two systems, mainly because drivers took longer to make the switch and across all three systems the first brake input came at about the 30 second mark, meaning there was no significant statistical difference in terms of the first brake input (*Q*: 0.13129, *p*: 0.87742). No significant statistical difference was found between the three systems for the amount of time to exit the highway either (*Q*: 1.47982, *p*: 0.24240).

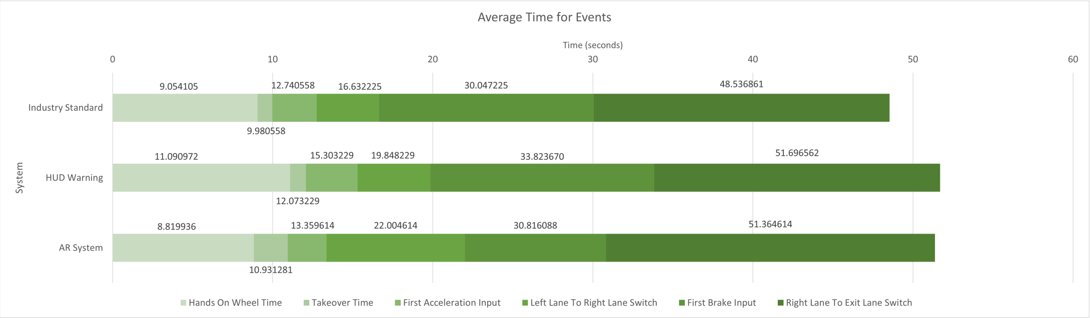


Figure 4.1: The average timestamp for when each event happened for the three systems.

4.2 Driving data

In this section we will present the results and statistical tests performed on the data collected while the user drove, divided into two subsections: one where we compare the data obtained after the user regained control, comparing the three approaches; and a second one where we compare the driving data compared after the user takes over to the driving before they initiate the automation, its baseline. All the tests performed in this section, and the next section, were one-way analysis of variance (ANOVA) due to the experimental design, to evaluate the effects of the systems (the independent variable) on any of the dependent variables collected, as we'll see below.

4.2.1 Comparison between approaches

In this subsection we will present the results obtained when comparing the driving data obtained, per approach, after the takeover moment. We've opted to divide the comparisons into two smaller sections, one for the comparisons between averages and another section for the comparisons between the measures standard deviations, as we'll see below.

4.2.1.A Averages

We've chosen the means of the acceleration and braking inputs to evaluate the participants driving tendencies, the mean absolute lane position to evaluate if the driver was more or less central in the lane and the mean speed to understand if any of the systems led to an alteration in how much speed drivers carried. When comparing the data collected before the drivers exited the highway no significant statistical difference was found between the 3 different systems for any of the measures, as we can see in table A.1 and figure 4.2.

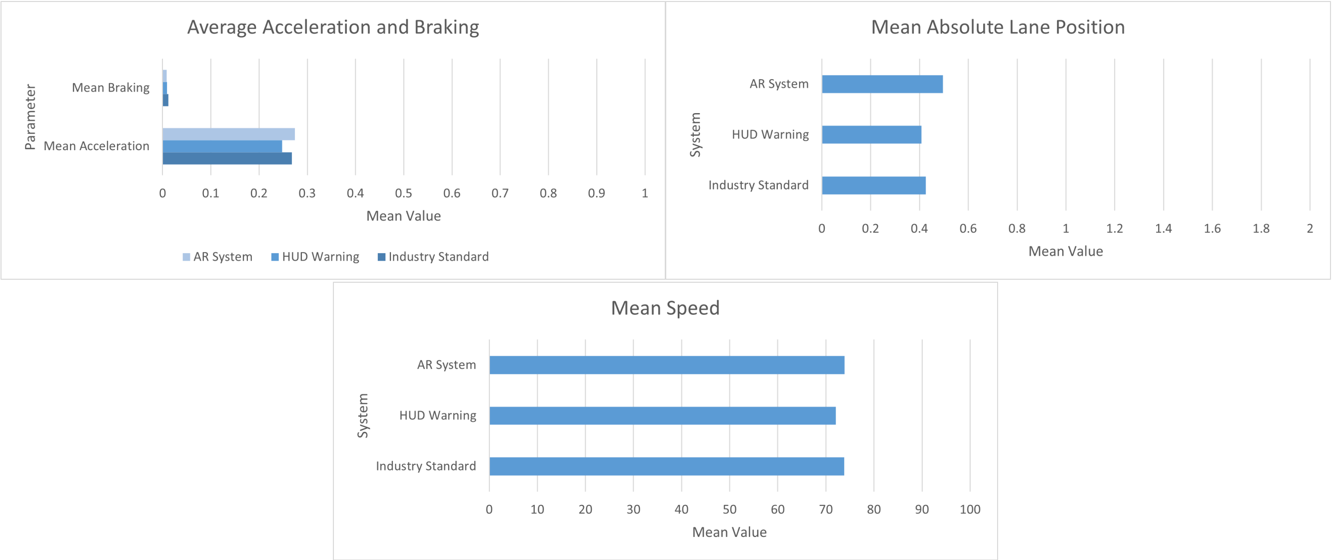


Figure 4.2: Comparison between approaches' mean values, for data collected before exiting the highway.

In the table A.1 and figure 4.3 we can observe that, no significant statistical difference was found between the 3 different systems for any of the four measures' mean values.

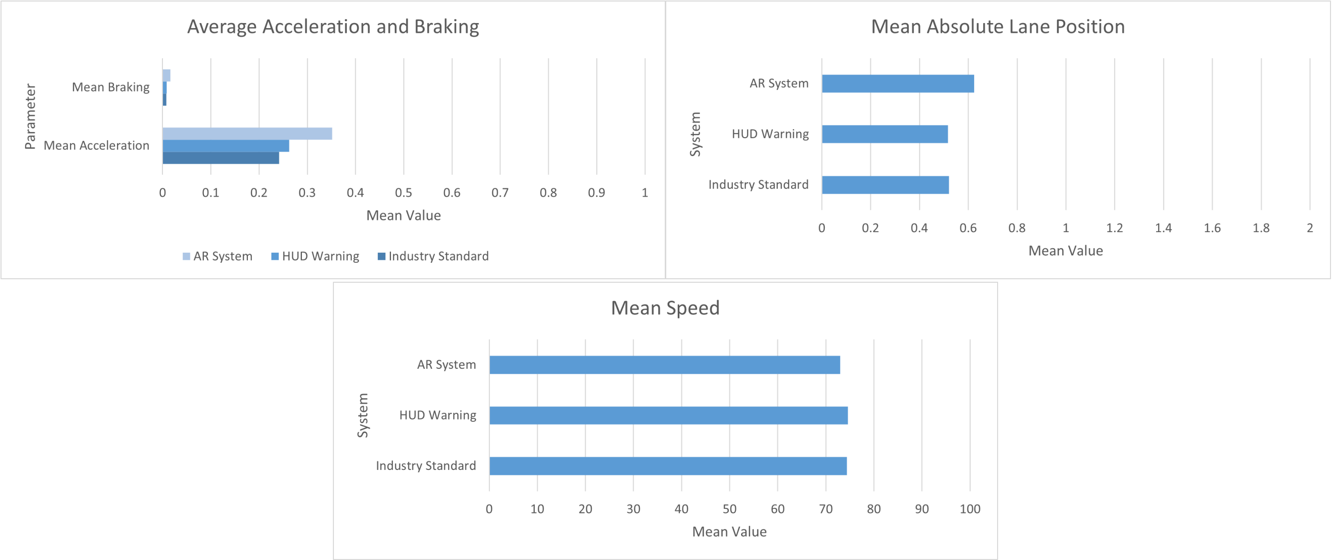


Figure 4.3: Comparison between approaches' mean values, for data collected before switching to the right lane.

In terms of the data collected inbetween the driver switching from the left lane to the right lane and then exiting the highway, i.e., when the driver was driving on the right lane before exiting the highway, no statistical difference was found in comparison of the mean values of the measures, between the 3 different systems, observable in figure 4.4 and table A.1.

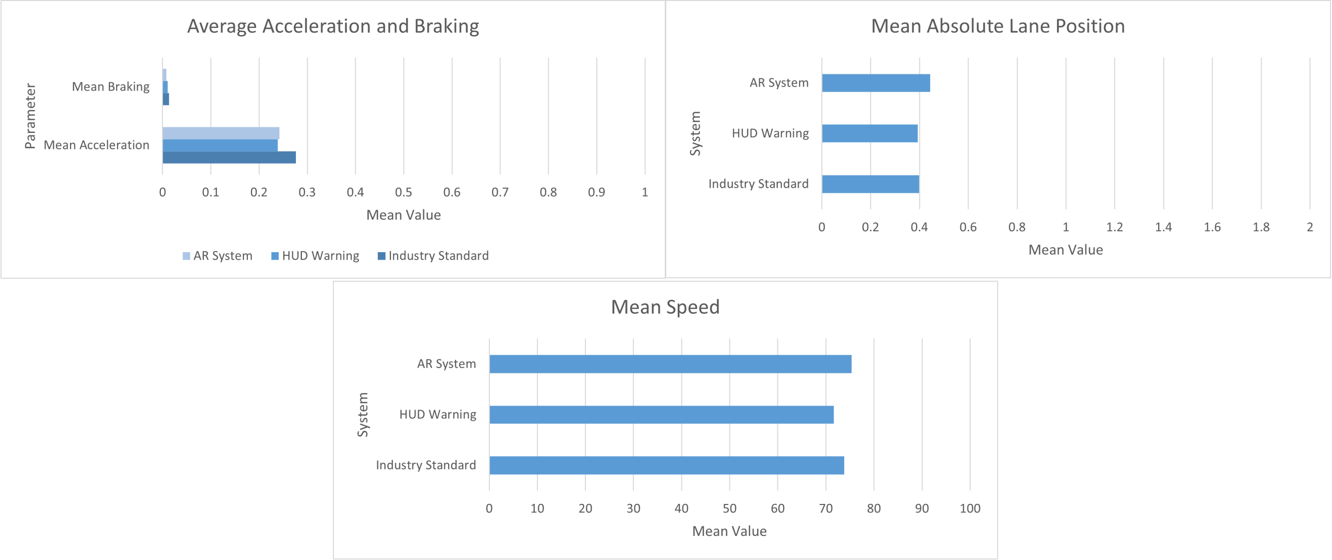


Figure 4.4: Comparison between approaches' mean values, for data collected inbetween the switches.

For the data collected during the first 5 seconds. all the way to the first 20 seconds no significant statistical difference was found for the average acceleration, braking, absolute lane position or speed, as we can see in table A.1. However, both in the first 25 seconds and first 30 seconds we found a significant statistical difference in the average absolute lane position, for the AR system compared to the other two, as we can observe in figures 4.5 and 4.6.

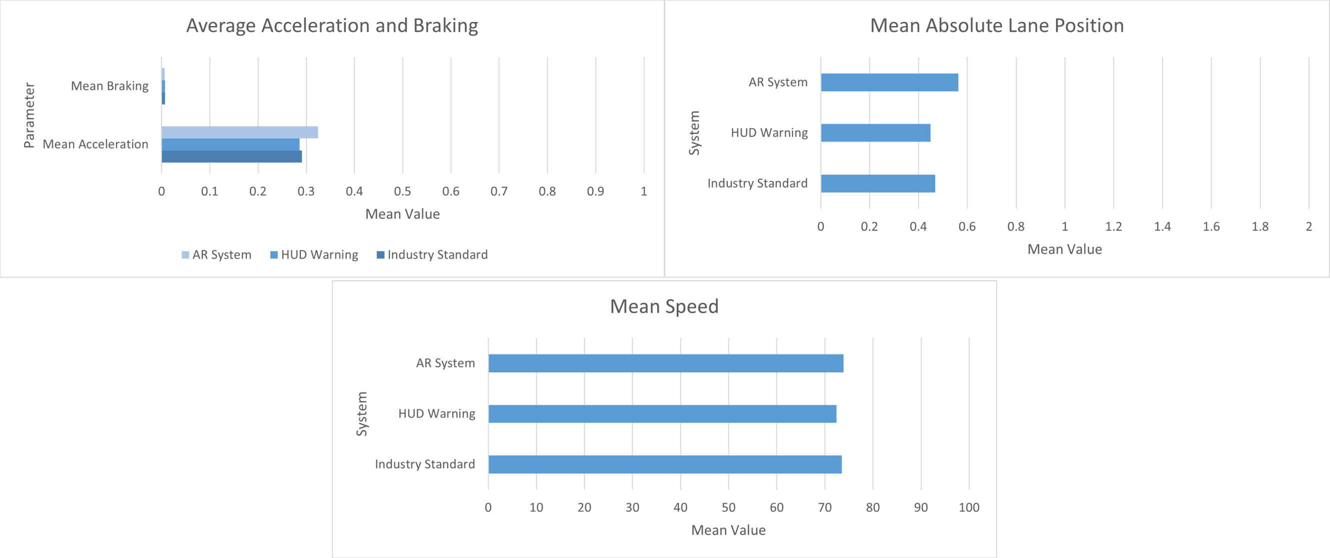


Figure 4.5: Comparison between approaches' mean values, for data collected in the first 25 seconds after taking over.

Figure 4.6: Comparison between approaches' mean values, for data collected in the first 30 seconds after taking over.

And for the data collected during the full 60 seconds after the user took over no statistical difference was found between the 3 different systems, as we can see table A.1 and in figure 4.7.

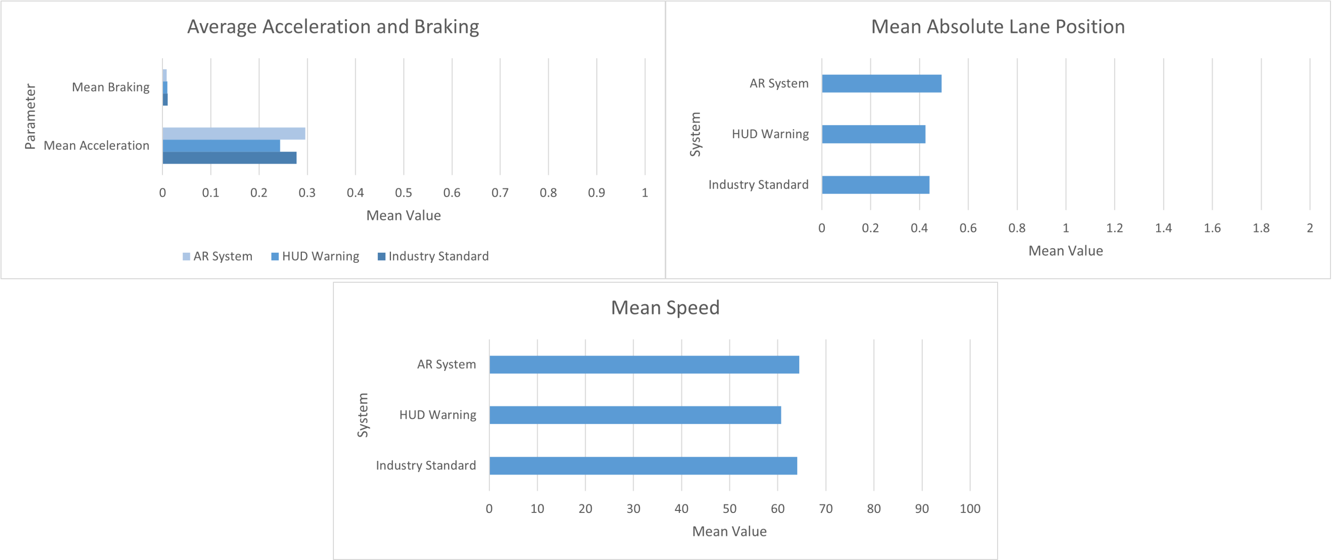


Figure 4.7: Comparison between approaches' mean values, for the full duration in which data was collected, after taking over.

4.2.1.B Standard Deviations

We opted to compare the standard deviations of the variables previously mentioned to evaluate if any of the systems led to a less consistent behaviour from the driver across any of the variables, along with the standard deviation of the steering angle, as it is common in studies like this, to see if participants were more or less smooth with their steering of the vehicle. For the data collected before the user exited the highway no significant statistical difference was found between the 3 different systems for any of the five measures, as we can see in table A.2 and figure 4.8.

Figure 4.8: Comparison between approaches' standard deviations, for data collected before exiting the highway.

For the data collected before the user switched from the left lane to the right lane no statistical difference was found in any of the standard deviations of the measures, between the 3 different systems, observable in table A.2 and in figure 4.9.

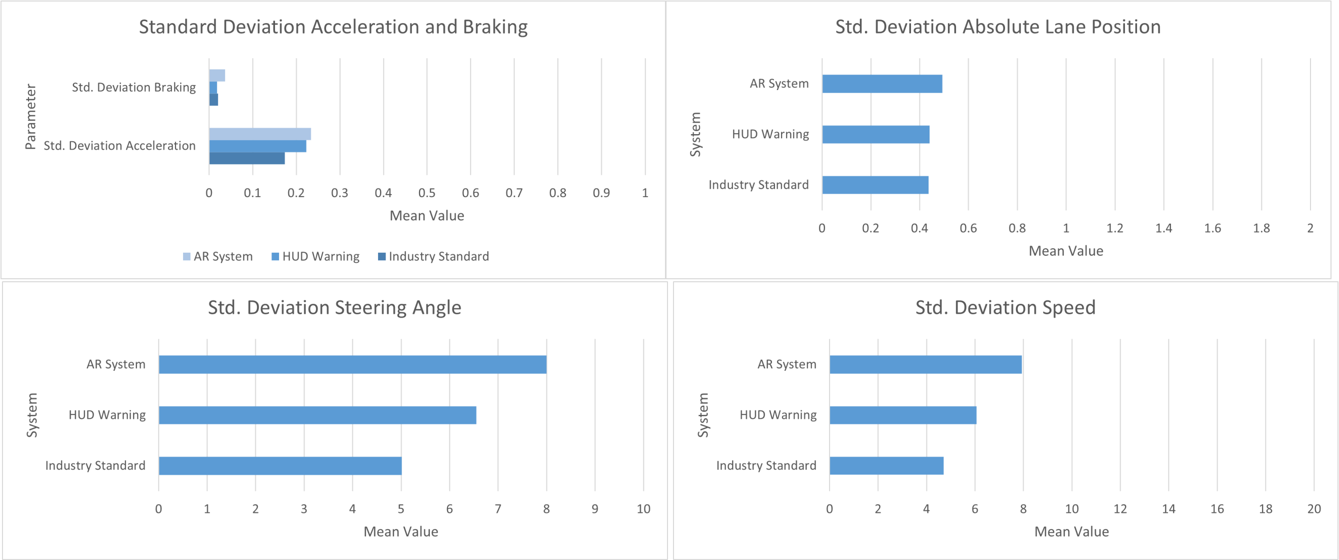


Figure 4.9: Comparison between approaches' standard deviations, for data collected before switching to the right lane.

For the data collected inbetween exiting the highway and switching from the left lane to the right lane no statistical difference was found between the 3 different systems, as we can see in table A.2 and figure 4.10.

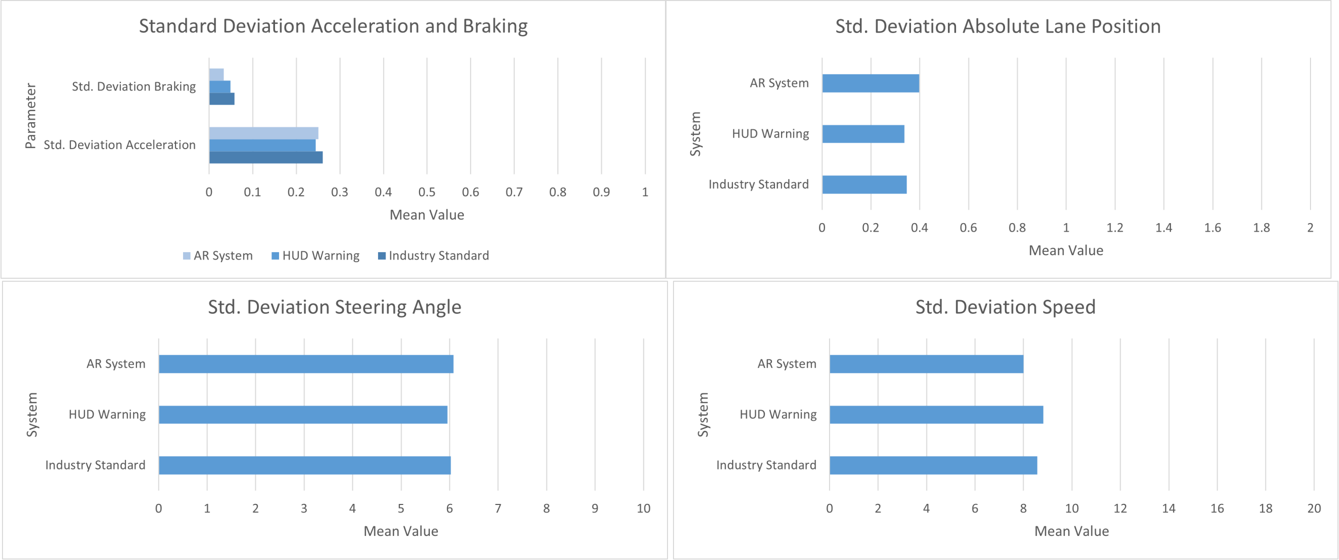


Figure 4.10: Comparison between approaches' standard deviations, for data collected inbetween the switches.

As we can observe in table A.2 no significant statistical difference was found between the three systems in the standard deviations of the five measures: acceleration, braking, steering angle, absolute lane position or speed in the first 5 seconds, all the way up to the first 30 seconds.

Finally, In figure 4.11 and in table A.2 we can observe that for the data collected during the full 60 seconds recorded after the user took back control of the vehicle we only found a significant statistical difference in the standard deviation of the absolute lane position due to users leaving the right lane and going into the left lane after exiting the highway, against our instructions.

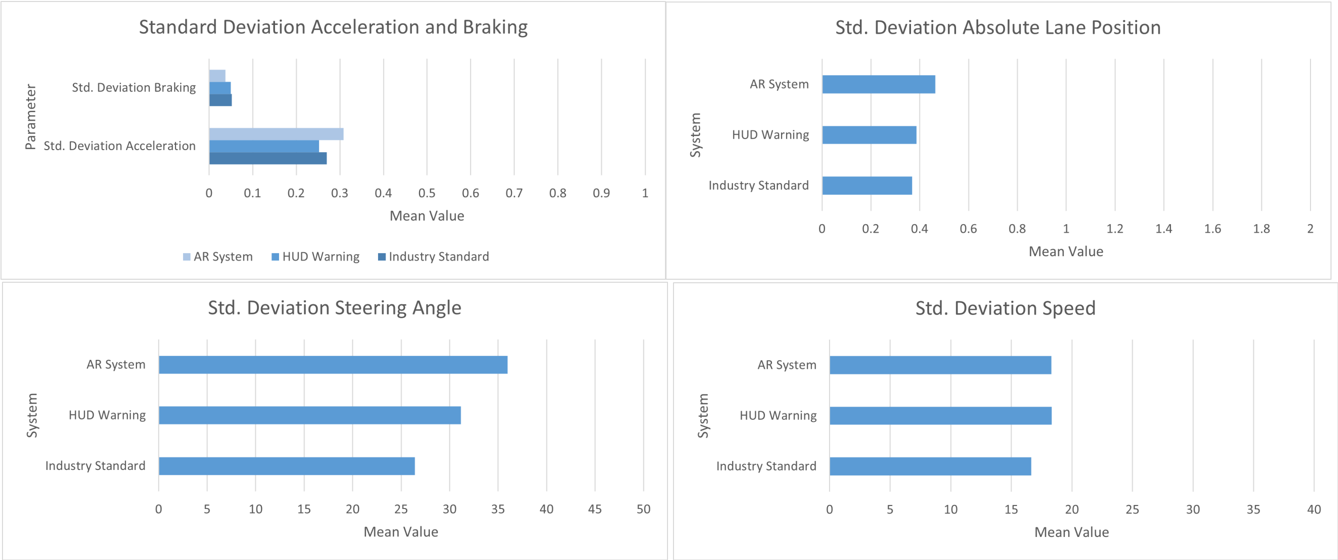


Figure 4.11: Comparison between approaches' standard deviations, for the full duration in which data was collected, after taking over.

4.2.2 Comparison to baseline

In this subsection we will present the results obtained when comparing the driving data obtained after the takeover moment and the driving data obtained before turning the automation on, the baseline. We've used the same dependent variables (comparing averages and standard deviations) mentioned before and also tested these sets of data using analysis of variance (ANOVA), just as before.

4.2.2.A Industry Standard

In this section we'll compare the driving participants did after being notified by the IS system's TOR, and taking over, to the driving participants did before the automated system was activated.

For the data collected before the user exited the highway a significant statistical difference was found in terms of the average braking, as is to be expected, because the user had to brake to slow down to make the exit safely, where as during the baseline drive the user didn't need to brake as much. We also found a significant statistical difference in the average absolute lane position but no significant statistical difference was found in terms of average acceleration or speed, observable in the table A.3 and in figure 4.12.

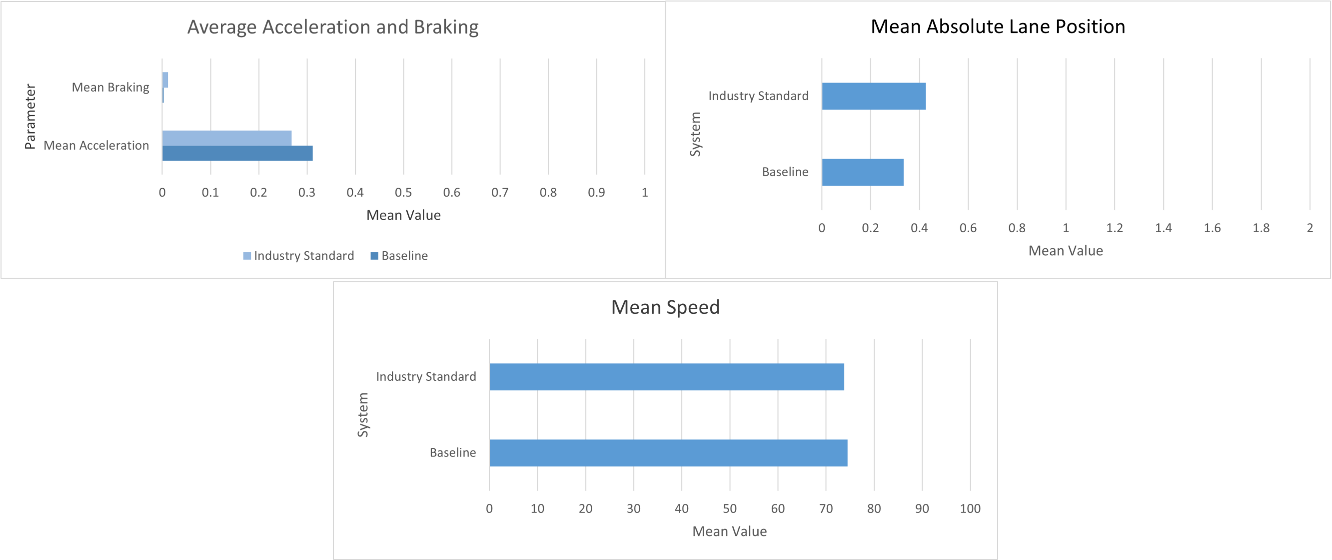


Figure 4.12: Comparison between baseline and Industry Standard driving mean values, for data collected before exiting the highway.

For the data collected before the user made the switch to the right lane a significant statistical difference was only found in terms of the average absolute lane position with no significant statistical difference found in the other three measures, as we can see in the table A.3 and in figure 4.13.

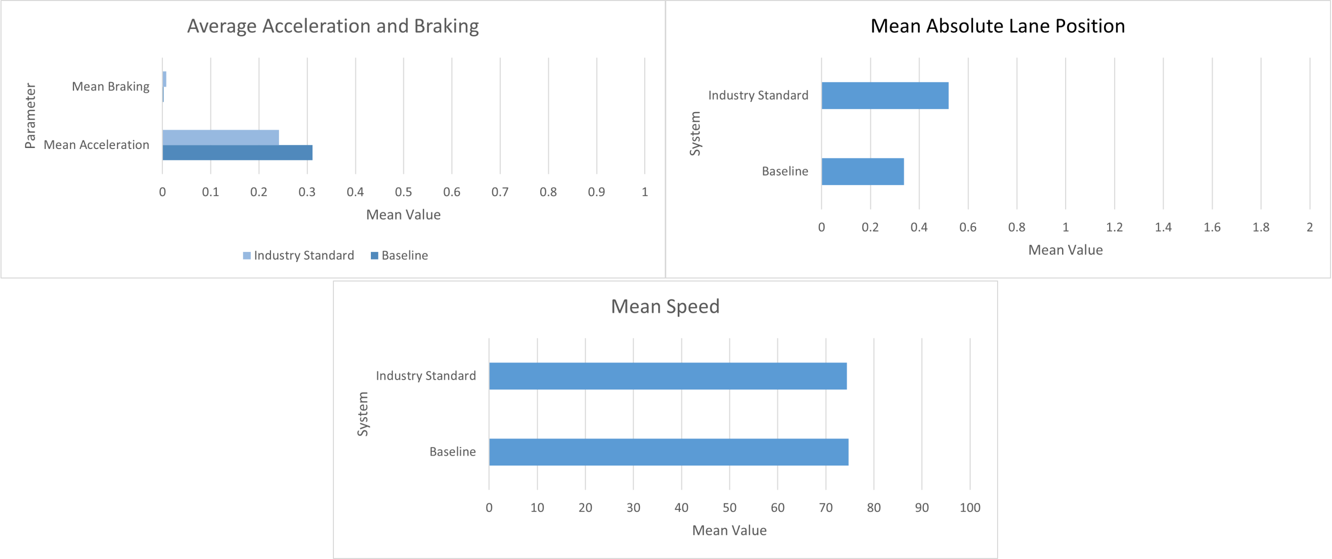


Figure 4.13: Comparison between baseline and Industry Standard driving mean values, for data collected before switching to the right lane.

In table A.3 and in figure 4.14 we can see that for the data collected before the user exited the highway and after he switched to the right lane, i.e., inbetween switches, which is the most accurate comparison to make with the baseline drive, a significant statistical difference was found in terms of the average braking as is to be expected. And for the other three measures' mean values no significant statistical difference was found.

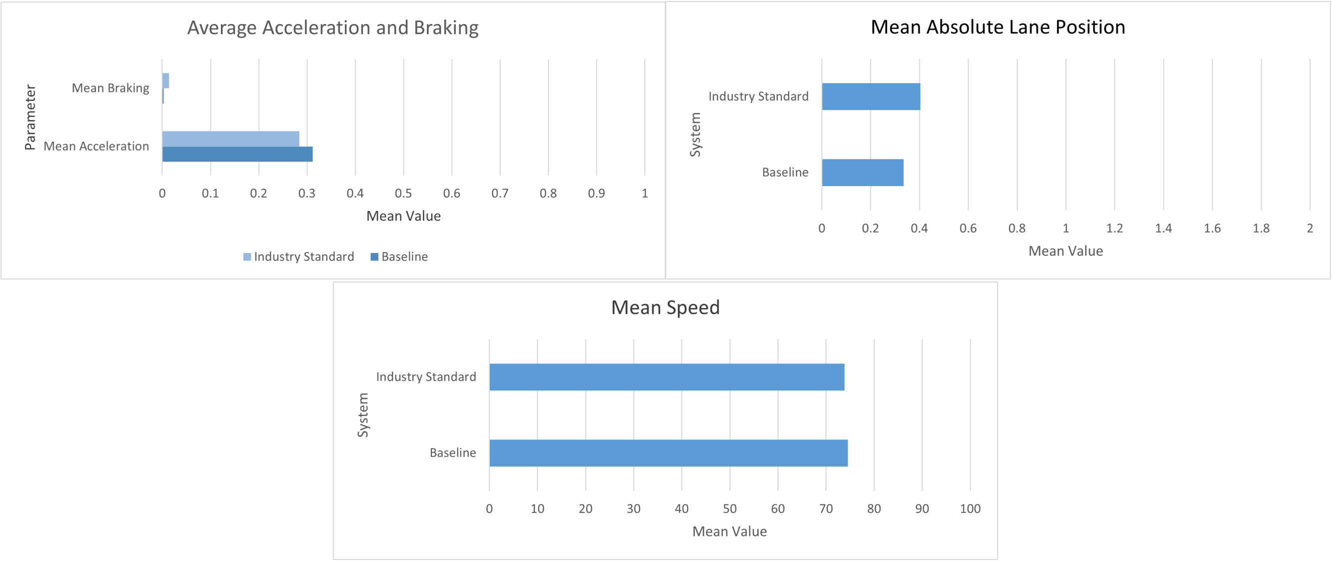


Figure 4.14: Comparison between baseline and Industry Standard driving mean values, for data collected inbetween the switches.

Comparing standard deviations now, for the data collected before the user exited the highway a significant statistical difference was found in terms of the standard deviation in braking and in in the standard deviation of absolute lane position, which, again, is to be expected, given the literature that says after a period of not driving the driver is not as used to the dynamics of the car. No significant statistical difference was found in terms of standard deviation of acceleration, steering angle or speed , observable in table A.4 and in figure 4.15.

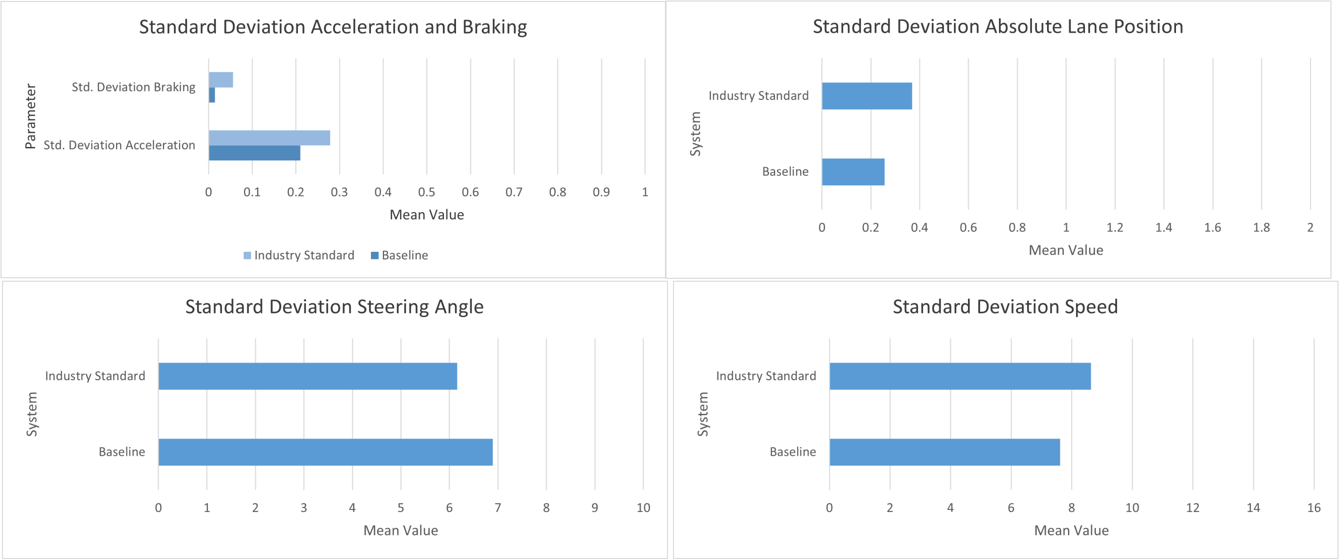


Figure 4.15: Comparison between baseline and Industry Standard driving standard deviations, for data collected before exiting the highway.

In table A.4 and in figure 4.16 we can see that for the data collected before the user made the move to the right lane a significant statistical difference was found in terms of the standard deviation in absolute lane position, steering angle and speed, which was expected, because the user had to switch to the right lane, which led to an increase in absolute lane position compared to the middle of the lane and steering angle, due to the need to steer right; the significant difference in standard deviation of speed occurred because the driver had to adjust his speed due to the car on the right lane, some users opted to brake/decelerate to slot in behind while others opted to speed up to overtake, leading to a wider variation in speed, hence the significant statistical difference. No significant statistical difference was found in the standard deviation of acceleration of braking.

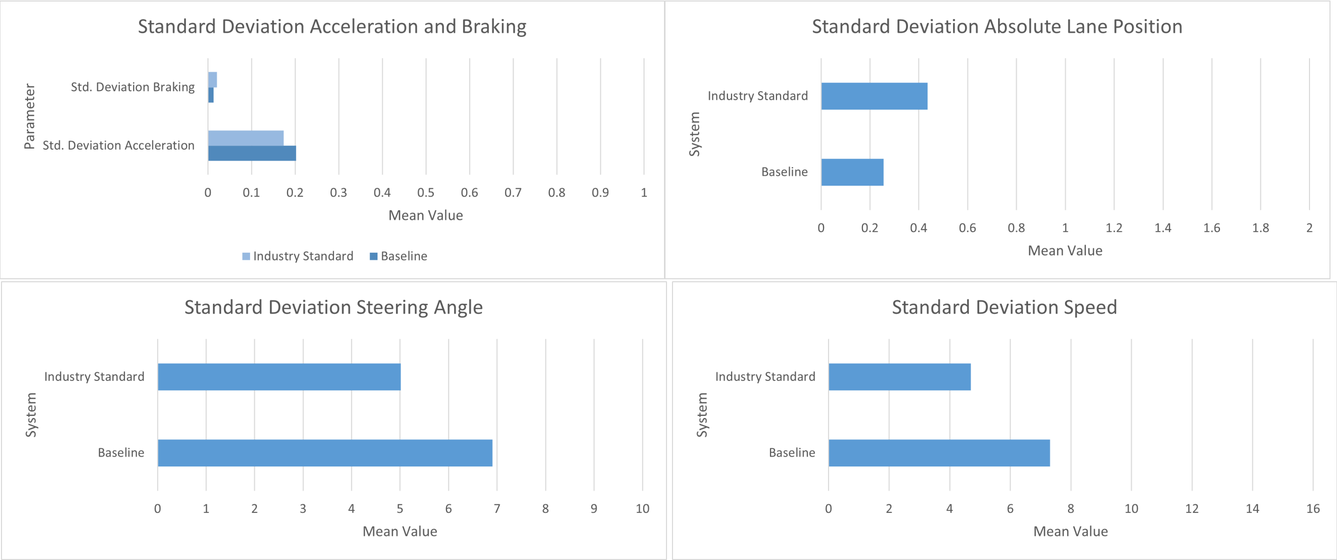


Figure 4.16: Comparison between baseline and Industry Standard driving standard deviations, for data collected before switching to the right lane.

In table A.4 and in figure 4.17 we can observe that for the data collected inbetween switches a significant statistical difference was found in terms of the standard deviation in braking which, again, is to be expected, and we also found a significant statistical difference in the standard deviation of absolute lane position, which, given the literature, was to be expected. No significant statistical difference was found in terms of standard deviation of acceleration, steering angle or speed.

Figure 4.17: Comparison between baseline and Industry Standard driving standard deviations, for data collected inbetween the switches.

4.2.2.B HUD Warning

In this section we'll compare the driving participants did after taking over from the HUD Warning system to the baseline driving done before turning on the automated system.

For the data collected before the user exited the highway a significant statistical difference was found in terms of the average braking, just as we found with the IS system, but contrary to the previous system, we also found a significant statistical difference in terms of average acceleration. No significant statistical difference was found for the mean values of the other two measures, as we can observe in table A.5 and in figure 4.18.

Figure 4.18: Comparison between baseline and HUD Warning driving mean values, for data collected before exiting the highway.

Just like with the Industry Standard system, a significant statistical difference was **only** found in terms of the average absolute lane position for the data collected before the user's switch to the right lane, as we can see in table A.5 and in figure 4.19.

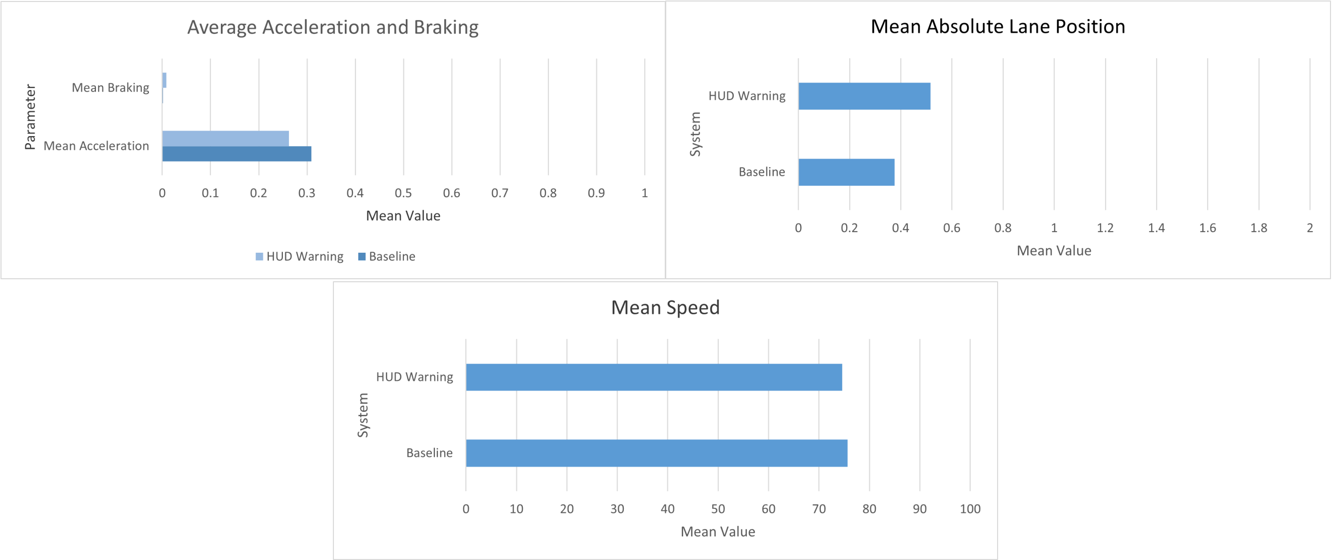


Figure 4.19: Comparison between baseline and HUD Warning driving mean values, for data collected before switching to the right lane.

While in table A.5 and in figure 4.20 we can see that, for the data collected inbetween the switches the user needed to make, a significant statistical difference was found in terms of the average braking, as expected; but a significant statistical difference was also found in terms of average acceleration, only not finding a difference for the average absolute lane position.

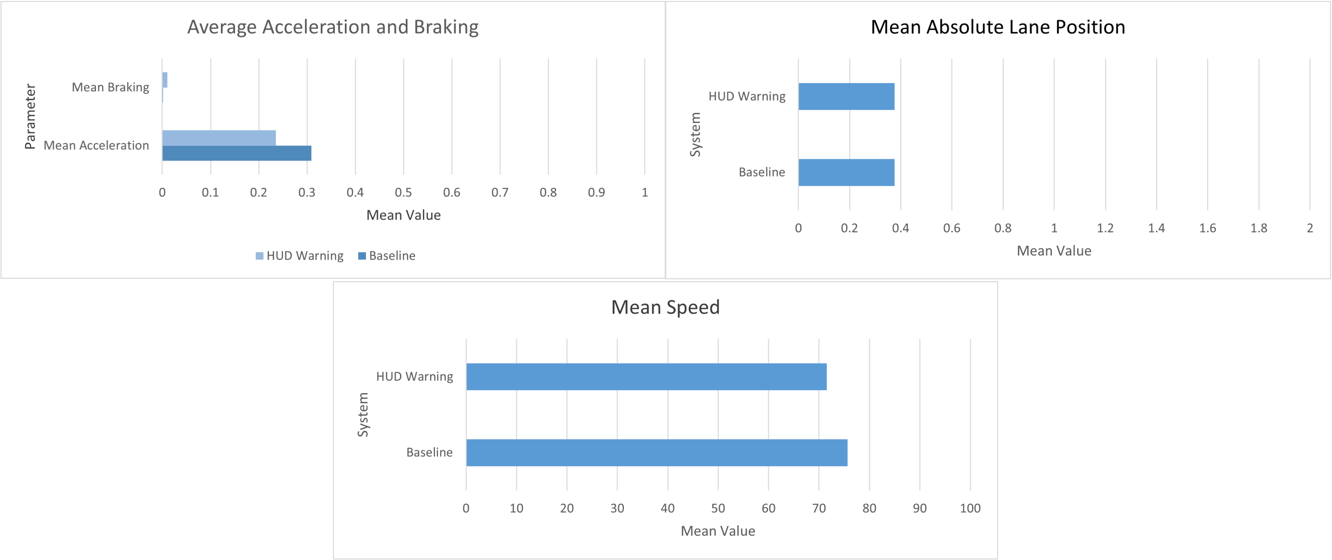


Figure 4.20: Comparison between baseline and HUD Warning driving mean values, for data collected inbetween the switches.

Moving on to the comparisons between the standard deviations, for the data collected before the user exited the highway a significant statistical difference was found in terms of the standard deviation in braking and absolute lane position, just as with the IS system. Adding to these, we also found a significant statistical difference in the standard deviation of speed, but no significant statistical difference was found in terms of standard deviation of acceleration or steering angle, observable in table A.6 and in figure 4.21.

Figure 4.21: Comparison between baseline and HUD Warning driving standard deviations, for data collected before exiting the highway.

For the data collected before the user made the manoeuvre to the right lane a significant statistical difference was **only** found for the standard deviation of the absolute lane position, observable in table A.6 and in figure 4.22.

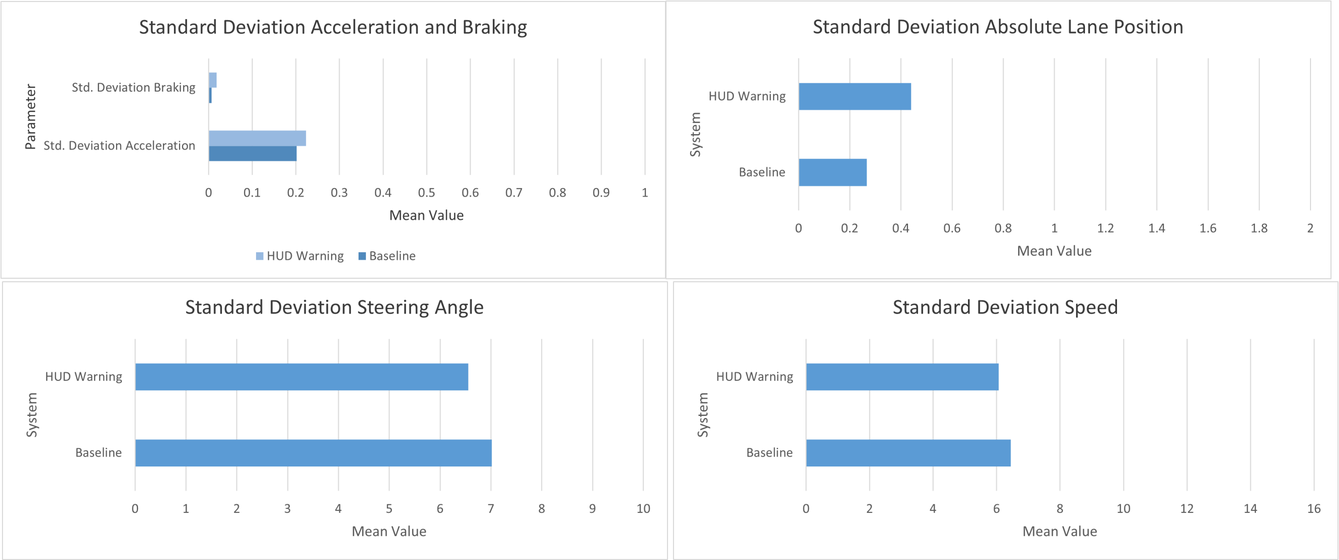


Figure 4.22: Comparison between baseline and HUD Warning driving standard deviations, for data collected before switching to the right lane.

For the data collected inbetween the manoeuvres a significant statistical difference was found in terms of the standard deviation in braking and in the standard deviation of absolute lane position, just like with the IS system; however, contrary to the previous system, a significant statistical difference was also found in terms of the standard deviation of speed; with no significant statistical difference found in terms of standard deviation of acceleration or steering angle, as we can see in table A.6 and in figure 4.23.

Figure 4.23: Comparison between baseline and HUD Warning driving standard deviations, for data collected inbetween the switches.

4.2.2.C AR system

Finally, in this section we'll compare the driving done after participants took over from the AR system to the driving done before turning on the automated system, the baseline drive.

In table A.7 and in figure 4.24 we can observe that, for the data collected before the user made the manoeuvre to leave the highway a significant statistical difference was found in terms of the average braking and average absolute lane position with no statistically significant difference found in the mean values of the other two measures.

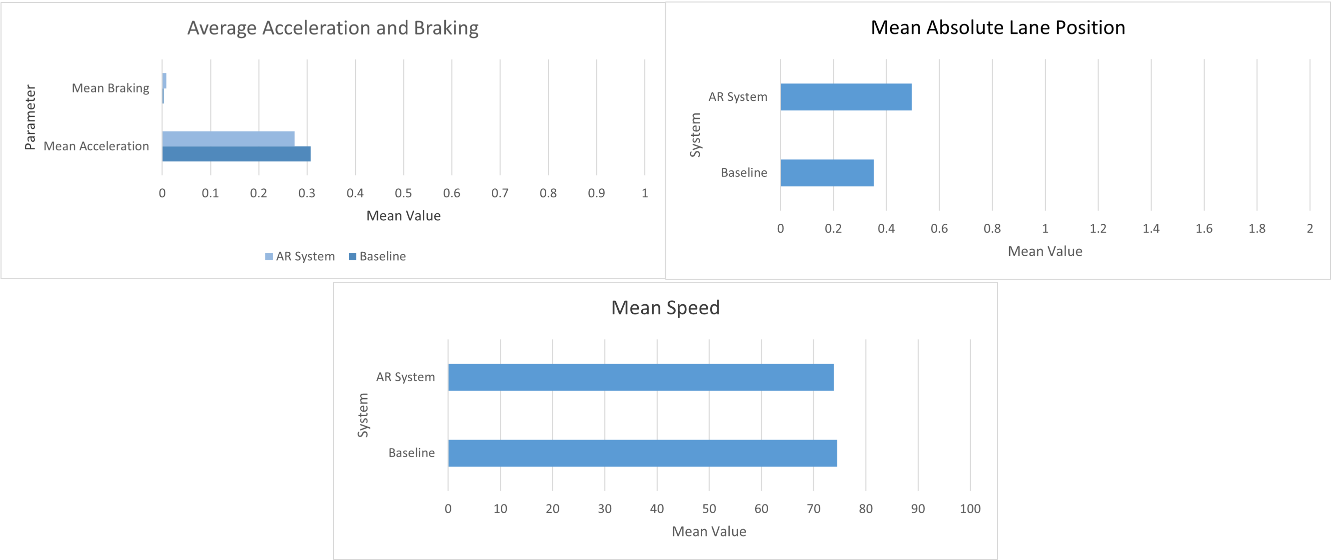


Figure 4.24: Comparison between baseline and AR system driving mean values, for data collected before exiting the highway.

For the data collected before the user made the manoeuvre from the left lane to the right lane we **only** found a significant statistical difference in the average absolute lane position, observable in table A.7 and in figure 4.25.

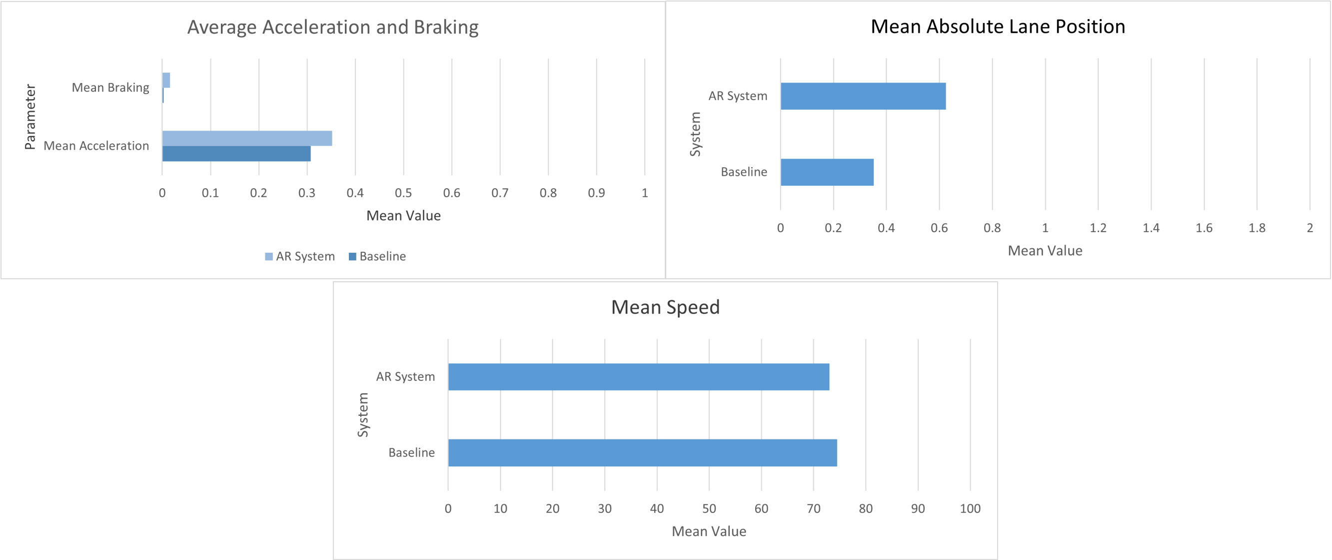


Figure 4.25: Comparison between baseline and AR system driving mean values, for data collected before switching to the right lane.

While in table A.7 and figure 4.26 we can see that for the data collected inbetween manoeuvres we found a significant statistical difference in the average acceleration and average absolute lane position. No statistically significant difference was found in terms of the average braking or speed.

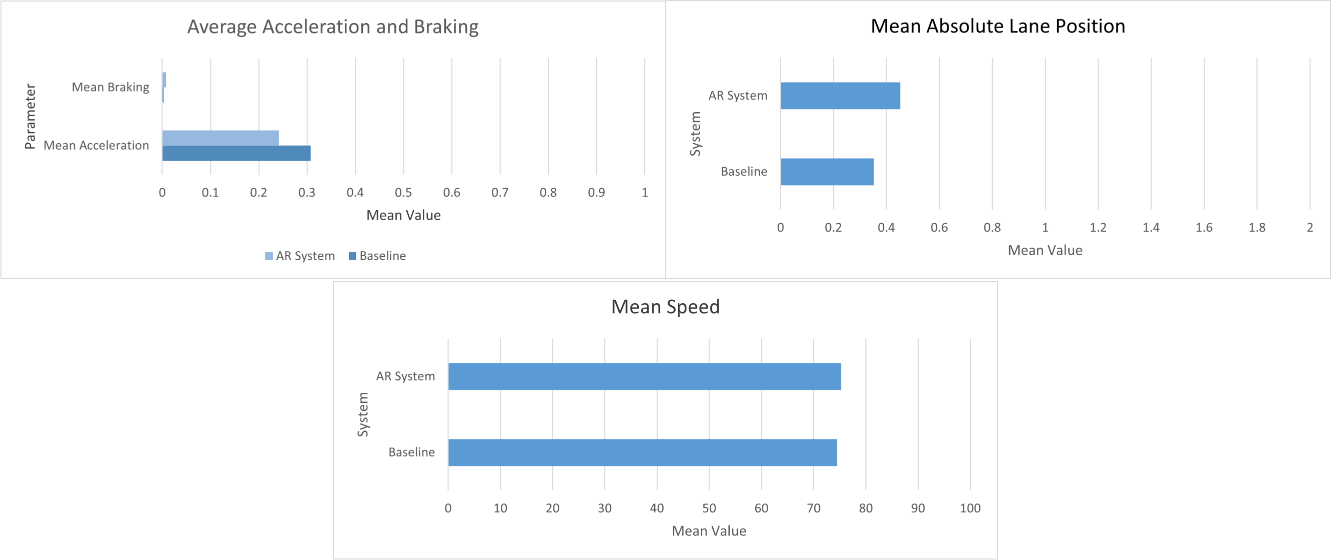


Figure 4.26: Comparison between baseline and AR system driving mean values, for data collected inbetween the switches.

Comparing the standard deviations now, for the data collected before the user exited the highway a significant statistical difference was found in terms of the standard deviation absolute lane position, just like with the other 2 systems, and there was also a significant statistical difference in the standard deviation of acceleration. No significant statistical difference was found in the standard deviation of braking, steering angle or speed, as we can observe in table A.8 and in figure 4.27.

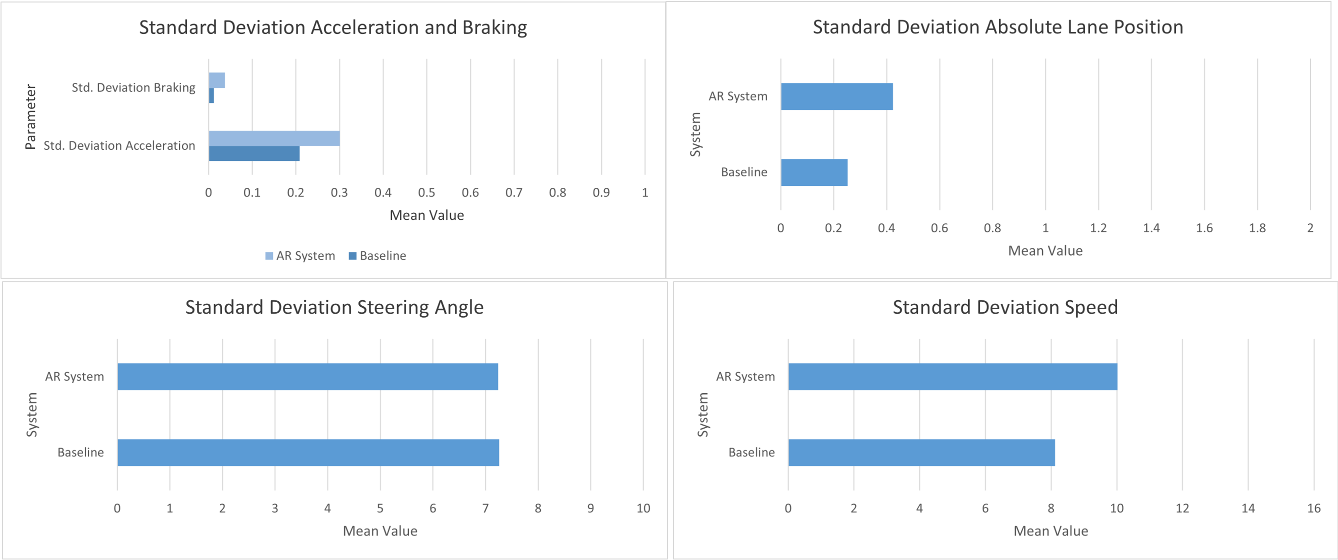


Figure 4.27: Comparison between baseline and AR system driving standard deviations, for data collected before exiting the highway.

For the data collected before the user switched from the left lane to the right lane a significant statistical difference was **only** found in terms of the standard deviation absolute lane position, just as we found with the HUD Warning system, as we can see in table A.8 and in figure 4.28.

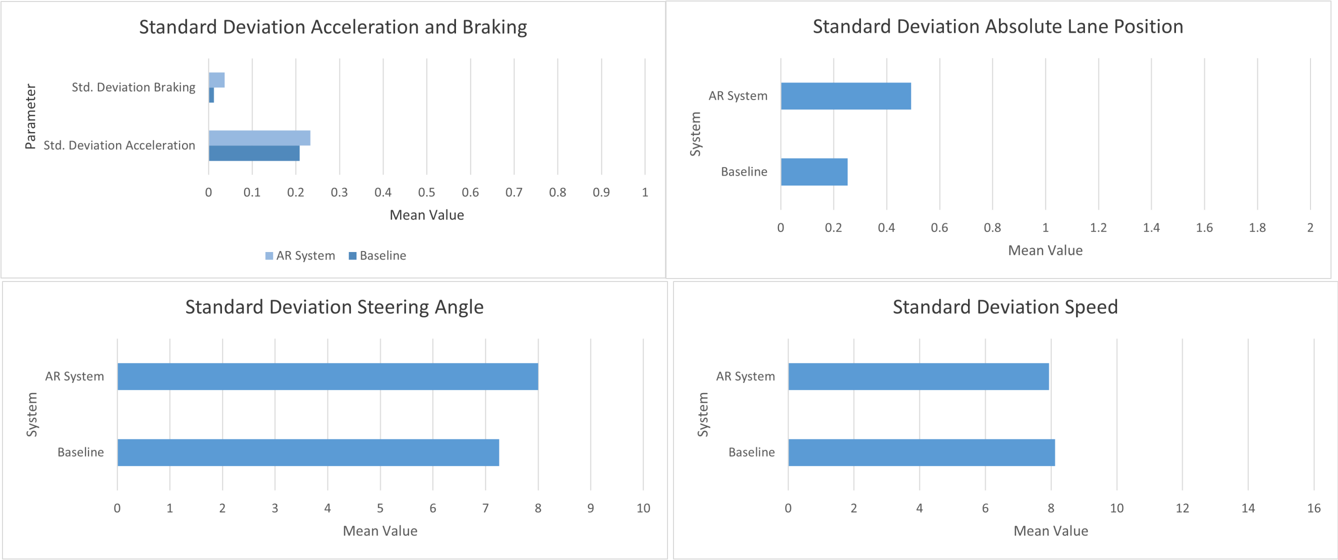


Figure 4.28: Comparison between baseline and AR system driving standard deviations, for data collected before switching to the right lane.

While in table A.8 and in figure 4.29 we can observe that for the data collected after the user entered the right lane and before he/she/them exited the highway a significant statistical difference was **only** found in terms of the standard deviation absolute lane position, just like with the HUD Warning system.

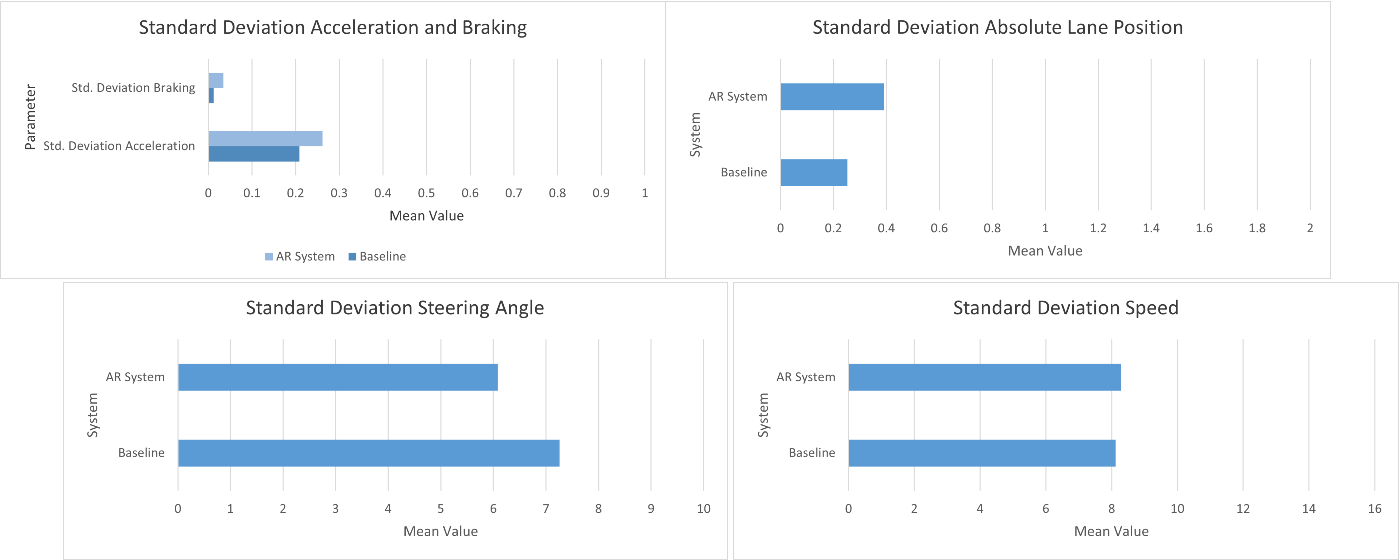


Figure 4.29: Comparison between baseline and AR system driving standard deviations, for data collected inbetween the switches.

4.3 Gaze data

In this section we will present the results and statistical tests performed on the **gaze** data collected after the TOR was emitted up until he finished the driving portion of the experiment, to examine if each system had an effect on the driver's behaviour. All the tests performed in this section were one-way analysis of variance (ANOVA), for the same reason mentioned as in the previous section. We opted to evaluate three things across all targets: how many times participants gazed at the points of interest on average, how long participants gazed, on average, at these points across the entire time (from the TOR to the end of the driving stint) and the average length of each glance towards the targets. These were the metrics chosen because we believe it would give us an indication of an alteration in driver behaviour by any of the systems; if any of the systems caused more gazes towards a particular target than the other systems or if drivers stared longer at a given target because of a change in the delivery of the TOR. To be noted in the following sections that the Exit indicator was only active during the AR system to not influence the results for the other 2 systems, since it was only in the AR system that it was active; we will use its data to compare to the other targets rather than the other approaches.

4.3.1 Individual Targets

In this subsection we will compare the results obtained, across the three metrics explained before, for each individual target: each mirror, each window, the center console, the HUD, the exit signs and the AR indicator between the three approaches. The results of the ANOVA statistical tests for this section can be observed in table B.1.

For the data collected for the left window, left mirror and rear view mirror no significant statistical difference was found when it came to the amount of times the user checked these. On the other hand, a significant statistical difference was found for the right window and right mirror, with the AR system producing slightly more gazes than the other 2 systems. For the amount of gazes towards the exit signs no significant statistical difference was found, neither for the one right before the exit nor the one 500 meters before the exit.

No significant statistical difference was found for the amount of gazes towards the instrument cluster behind the wheel nor the gazes towards the tablet; but we did find a significant statistical difference in the amount of gazes towards the HUD and the center console, with the HUD Warning system producing the more gazes towards these two targets, as expected. Considering the total amount of gazes towards all targets, no significant statistical difference was found, observable in figure 4.30.

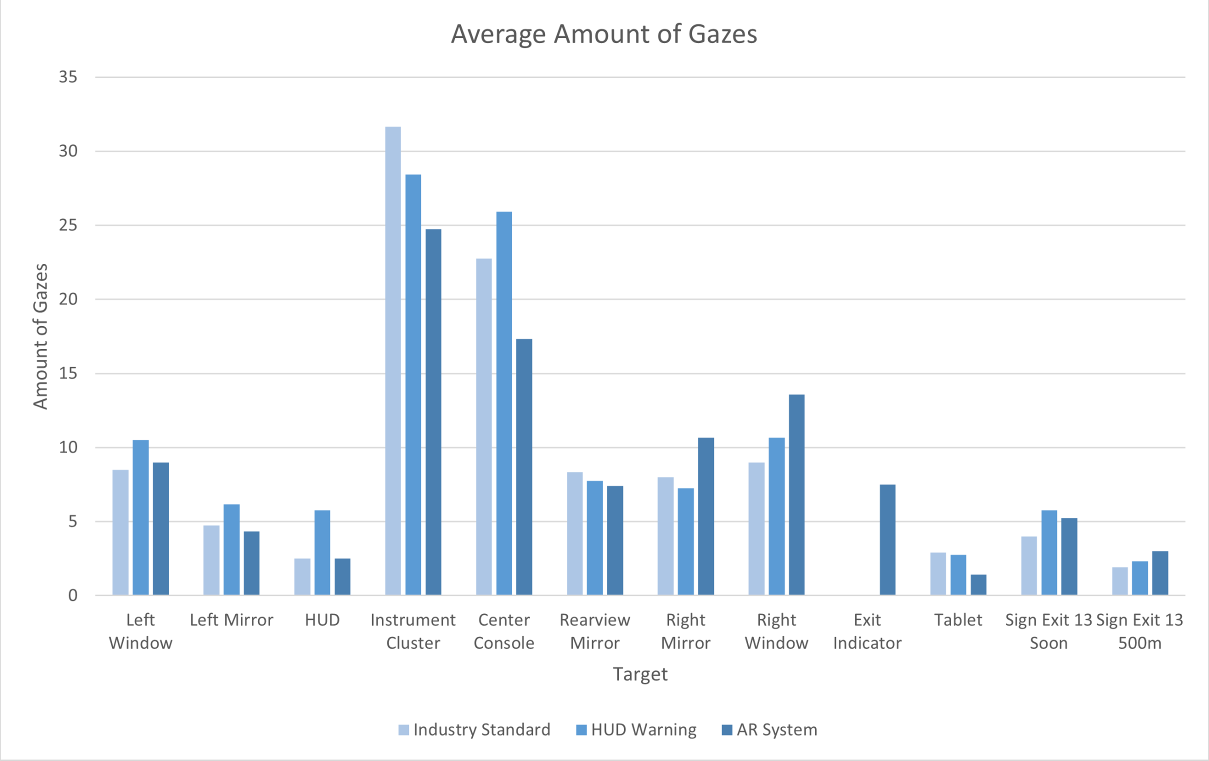


Figure 4.30: The average amount of gazes for each individual target.

For the total dwell time on the targets data collected no significant statistical difference was found for the left window, left mirror or rear view mirror. Even though there was a difference in the amount of gazes, in terms of total dwell time no significant statistical difference was found for the right window or right mirror. No significant statistical difference was found for the exit signs, neither for the one right before the exit nor the one 500 meters before the exit.

No significant statistical difference was found for the total dwell time on the instrument cluster behind the wheel nor the dwell time on the tablet; but we did find a significant statistical difference in dwell time on the HUD and the center console, just as with the amount of gazes, as expected. Considering the total dwell time across all targets, no significant statistical difference was found. To be noted that the total dwell time on the exit indicator was higher than the other targets, apart from the exit signs, as seen in figure 4.31.

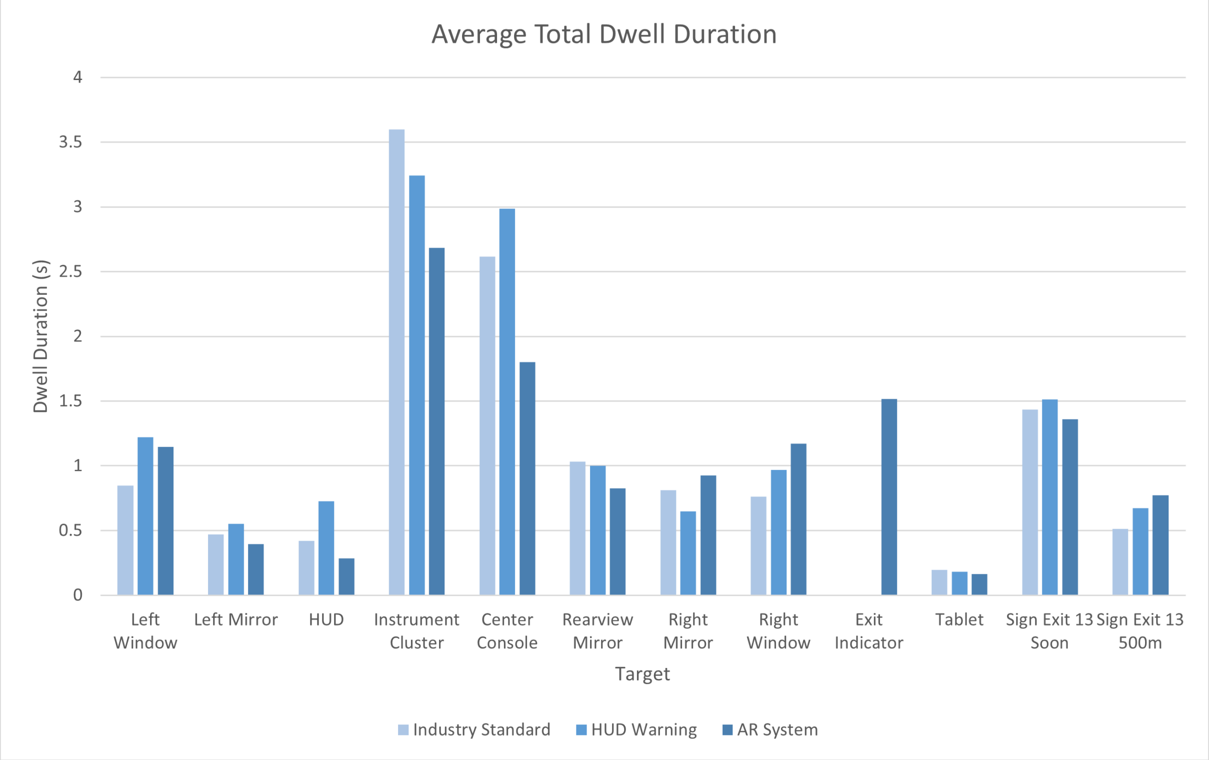


Figure 4.31: The average total dwell time of the users on each individual target.

For the average glance duration for each target, again, no significant statistical difference was found for the left window, left mirror, rear view mirror, right window or right mirror. No significant statistical difference was found in average glance duration for the exit signs either.

No significant statistical difference was found for the average glance duration on the instrument cluster behind the wheel nor on the tablet and, unlike the amount of gazes and total dwell time, no significant statistical difference was found for the average glance duration on the HUD or the center console. Considering the average glance duration for each target no significant statistical difference was found, observable in figure 4.32.

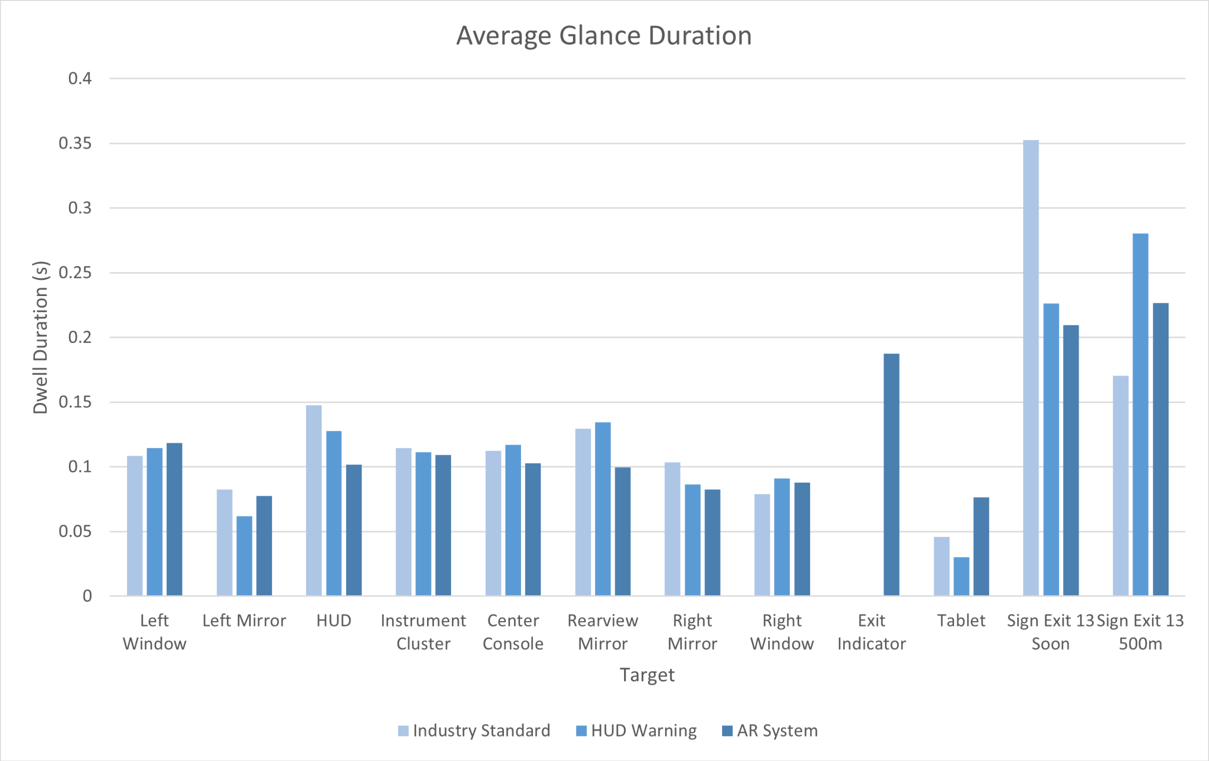


Figure 4.32: The average amount of time each glance lasted on each individual target.

4.3.2 Grouped Targets

In this subsection we will compare the results obtained when grouping the targets, i.e., the data for all the mirrors, for both windows, for the interior (consisting of the instrument cluster and center console), the digital targets and the exit signs. The results of the ANOVA statistical tests for this section can be observed in table B.2.

In figure 4.33 we can see that for the data collected for the total amount of gazes no significant statistical difference was found for the mirrors, windows or the exit signs. On the other hand, a significant statistical difference was found for the total amount of gazes towards the interior targets and the digital ones, though this difference may be due to the exit indicator only being present for the AR system. In terms of total amount of gazes across all groups no significant statistical difference was found.

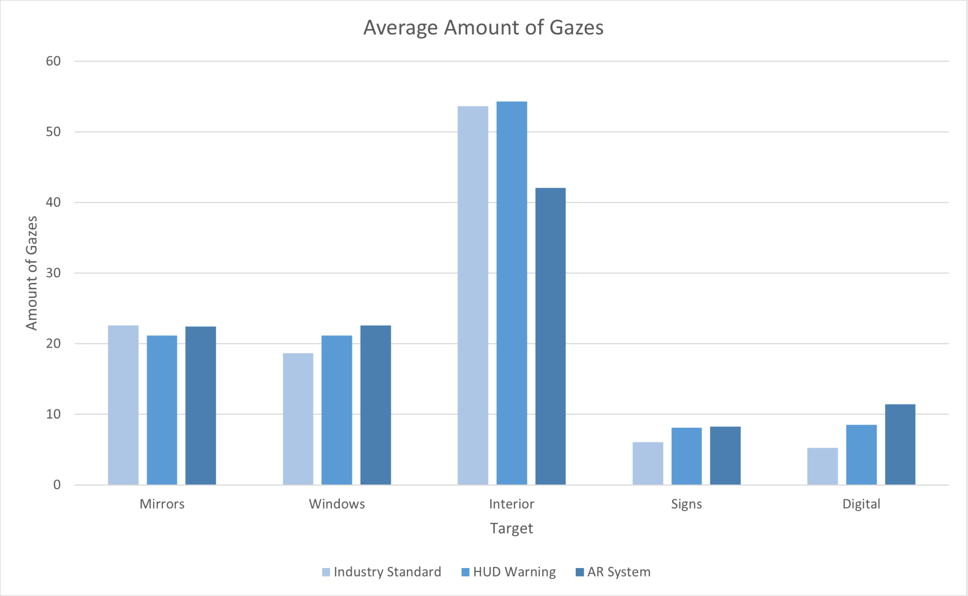


Figure 4.33: The average amount of gazes on each group of targets.

For the data collected in terms of total dwell time no significant statistical difference was found for the mirrors, windows or the exit signs. Just as with the total amount of gazes, a significant statistical difference was found for the interior targets and the digital ones. In terms of total dwell time across all groups no significant statistical difference was found, observable in figure 4.34.

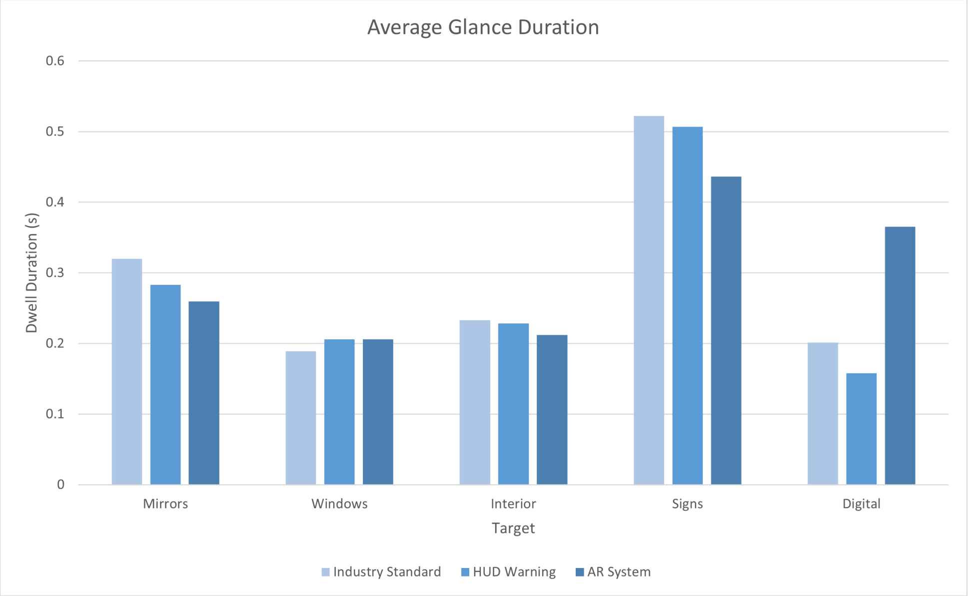


Figure 4.34: The average total dwell time of the users on each group of targets.

For the data collected in terms of average glance duration no significant statistical difference was found for the mirrors, windows or the exit signs. Unlike the previous two metrics no significant statistical difference was found for the interior targets, but we did find, again, a significant statistical difference for the digital targets. In terms of average glance duration across all groups no significant statistical difference was found, seen in figure 4.35.

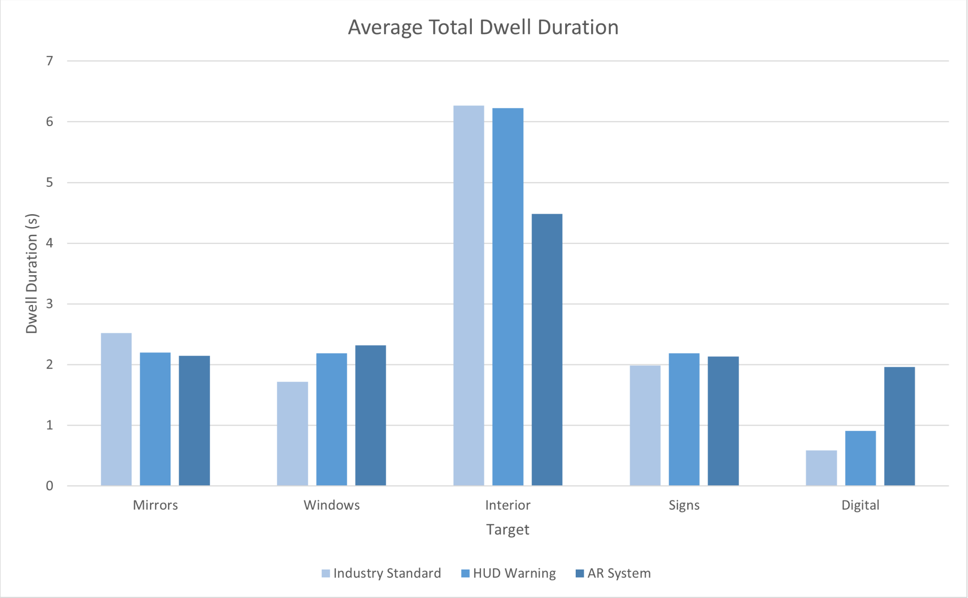


Figure 4.35: The average amount of time each glance lasted on each group of targets.

In figure 4.36 we can observe that for the data collected in terms of total dwell time towards the road/other locations not tracked, which is an estimation, no significant statistical difference was found (Q: 0.98293, p: 0.38490).

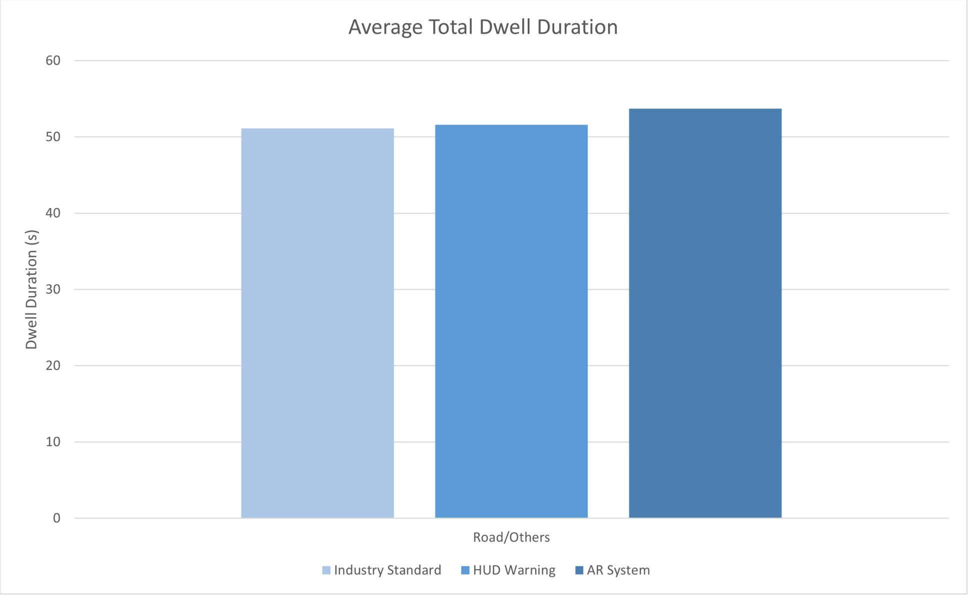


Figure 4.36: The estimated average total dwell time of the users on the road and other non tracked targets.

4.4 User Experience

In this section we'll present the results obtained from the user's responses to three forms they filled out after testing each system, to see if either of the systems had an influence in the user's experience. In order to test statistical difference Friedman tests were carried out on the data collected since these involved ranked measurements, as opposed to the data collected in the previous sections.

4.4.1 NASA-TLX

In order to evaluate the workload each system imposed on the user they filled out the NASA's Task Load Index (NASA-TLX) questionnaire and in this section we present the results obtained for each parameter.

In terms of the overall workload no significant statistical difference was found and the same can be said for each individual parameter evaluated by the NASA-TLX questionnaire: mental demand, physical demand (expected since there was little to no physical demand since the participant simply sat down during the entirety of the experiment), temporal demand, the user's perceived performance, the user's effort or the frustration caused by each system, as we can see in the box and whisker chart in figure 4.37 and in table B.3. Although, of all the parameters measured, frustration was the one where the most difference was found between the three systems with the AR system causing the least frustration to the users, even though the test did not return a significant difference.

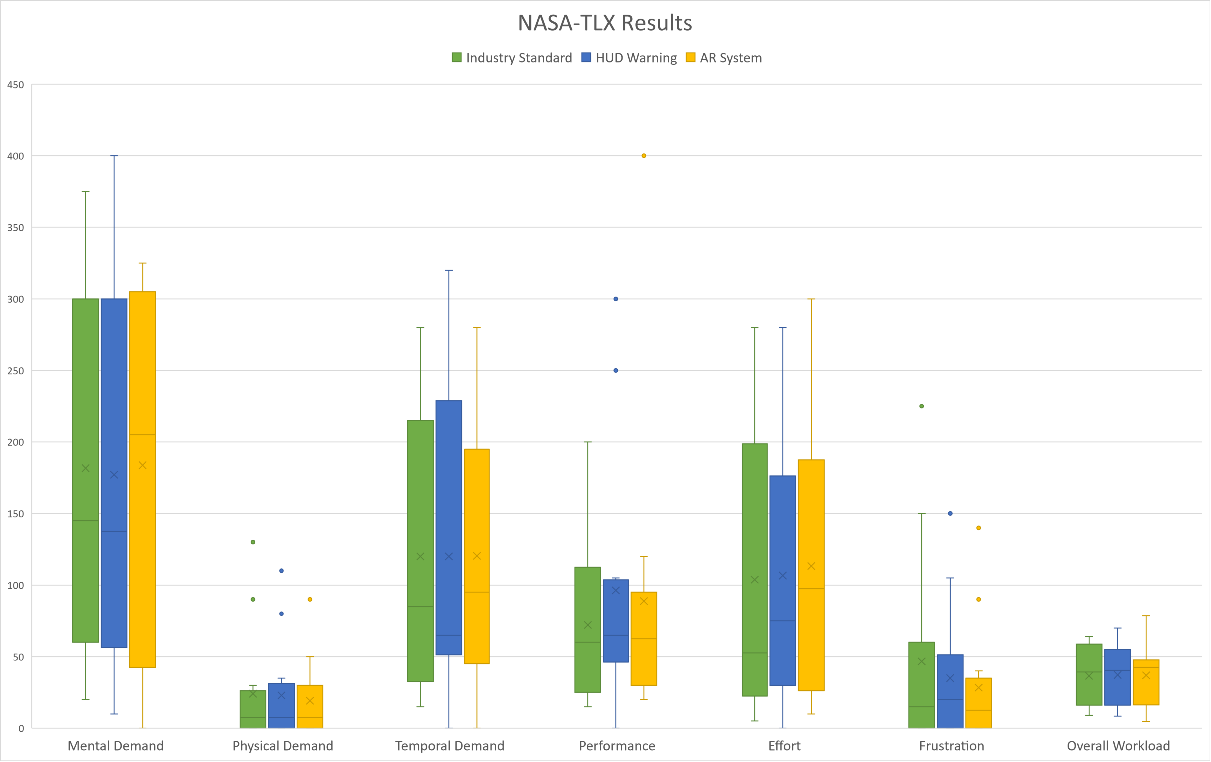
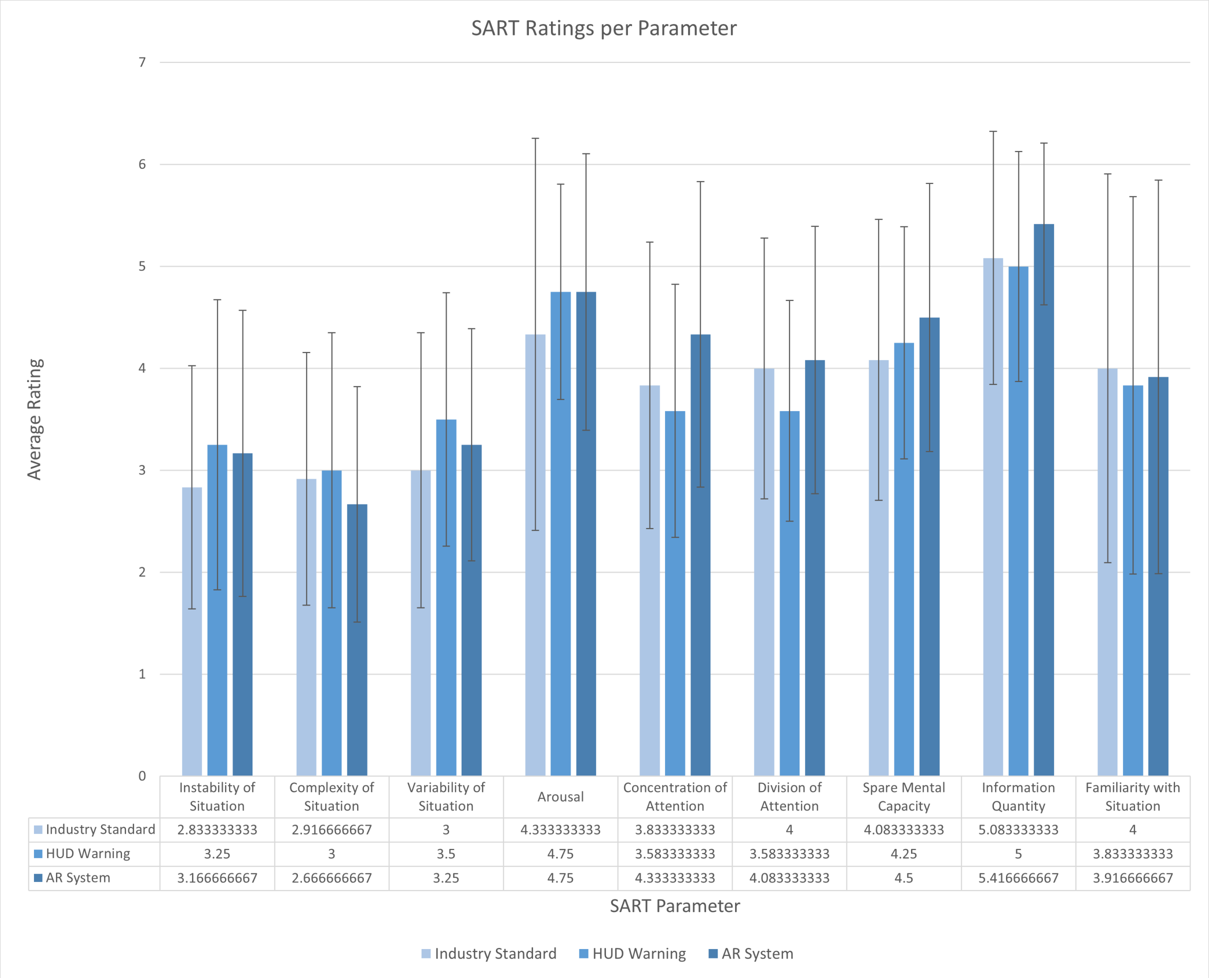


Figure 4.37: A box and whisker chart depicting the results obtained for each parameter of the NASA-TLX quiz and the overall workload.

4.4.2 SART

In order to evaluate the participant's awareness of the world around him after taking over, and the user awareness of the situation as a whole, the participant filled out he Situation Awareness Rating Technique (SART) form after the completion of the experiment with each system.

Just like with the NASA-TLX form, no significant statistical difference was found for any of the parameters evaluated by the questionnaire: instability of the situation, complexity of the situation, variability of the situation, arousal, concentration of attention, division of attention, spare mental capacity the participant had facing the situation, information quantity or familiarity with the situation, as we can see in table B.4 and in figure 4.38.

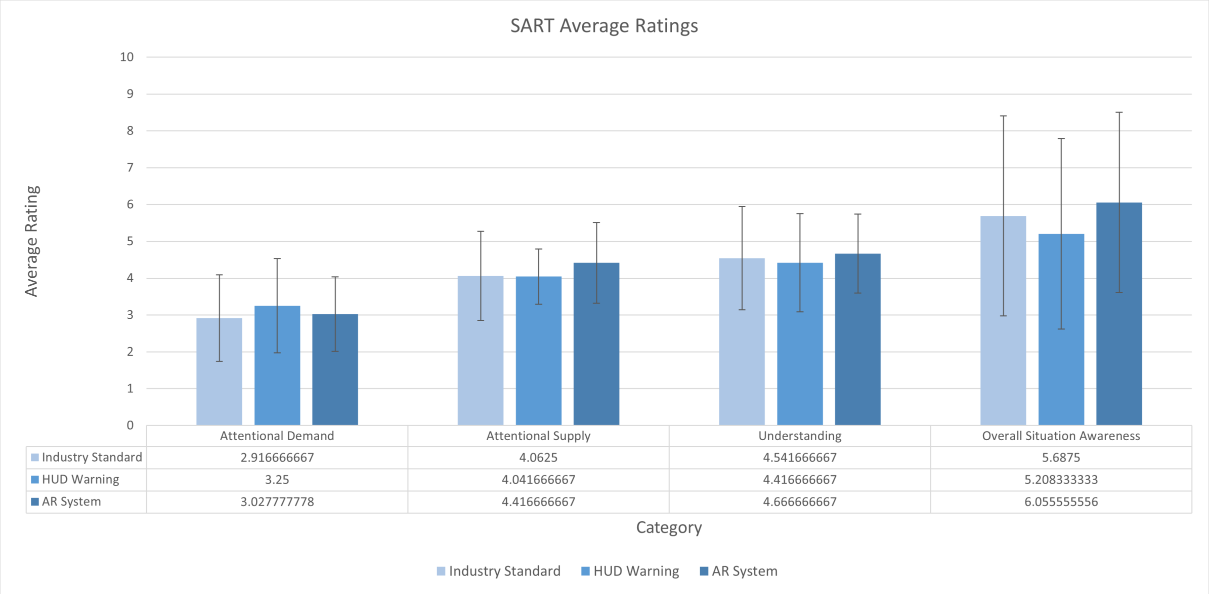


	Instability of Situation	Complexity of Situation	Variability of Situation	Arousal	Concentration of Attention	Division of Attention	Spare Mental Capacity	Information Quantity	Familiarity with Situation
Industry Standard	2.833333333	2.916666667	3	4.333333333	3.833333333	4	4.083333333	5.083333333	4
HUD Warning	3.25	3	3.5	4.75	3.583333333	3.583333333	4.25	5	3.833333333
AR System	3.166666667	2.666666667	3.25	4.75	4.333333333	4.083333333	4.5	5.416666667	3.916666667

Figure 4.38: The average responses for each parameter of the SART, with the standard deviation as error bars.

Another possibility with the SART is combining the individual parameters into three major groups: the situation's instability, complexity and variability can be combined into **Attentional Demand**; arousal, concentration of attention, division of attention and spare mental capacity can be combined into **Attentional Supply**; and information quantity and familiarity with the situation can be combined into the user's **Understanding** of the situation. When averaging the combination of the individual parameters into each group, no significant statistical difference was found for attentional demand, attentional supply or understanding, observable in table B.4 and in figure 4.39.

Finally, the SART also allows to evaluate overall situation awareness using a formula involving the previous three groups mentioned: **Situation Awareness** = Understanding - (Demand - Supply). Applying this formula to obtain a measure of the participant's situation awareness for each system, and comparing the averages for the three systems, no significant statistical difference was found between the three systems, as we can observe in table B.4 and in figure 4.39.

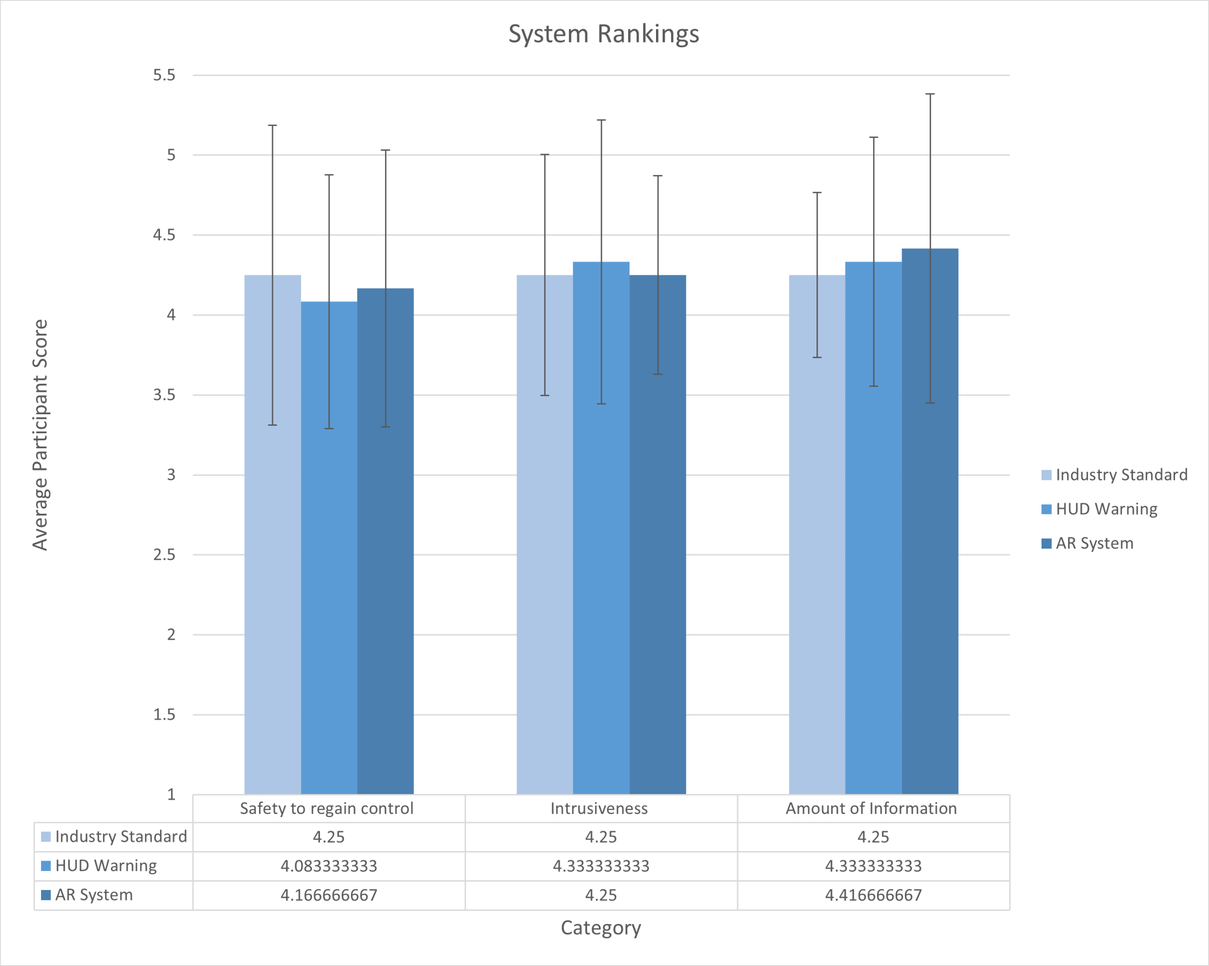


	Attentional Demand	Attentional Supply	Understanding	Overall Situation Awareness
Industry Standard	2.916666667	4.0625	4.541666667	5.6875
HUD Warning	3.25	4.041666667	4.416666667	5.208333333
AR System	3.027777778	4.416666667	4.666666667	6.055555556

Figure 4.39: The average value for Attentional Demand, Attentional Supply, Understanding and overall Situation Awareness, with the standard deviation as error bars.

4.4.3 System safety

To finish each system's experiment, the user filled out a short form designed by the authors to evaluate the amount of information each system gave to the user, how intrusive the system was and if the amount of information provided by the system, combined with the way the system provided said information was enough to guarantee a safe transfer of control. The participants answered these three questions in the form of a 5 point Likert scale and no significant statistical difference was found for either of the three questions proposed to the participant: if the information provided was enough, the intrusiveness of the system and how safe the participant felt the system was, given the information and the way it was conveyed, as we can see in table B.5 and in figure 4.40.



	Safety to regain control	Intrusiveness	Amount of Information
Industry Standard	4.25	4.25	4.25
HUD Warning	4.083333333	4.333333333	4.333333333
AR System	4.166666667	4.25	4.416666667

Figure 4.40: The average response by the participants to the short form, with the standard deviation as error bars.

In the next section we'll discuss what we gathered from these results and how they prove, or disprove, the hypotheses we formulated at the beginning of this work.

5

Discussion

Contents

In this penultimate chapter we'll discuss our findings on the data presented in the previous 4 section. First we'll discuss the driving performed after the participant took over, how and if each system tested influenced their driving and our findings when comparing the participant's driving with the baseline drive performed before turning the automation on. Next we'll discuss the effects on driver behaviour, based on the driver's gaze data (collected after the takeover request (TOR) was issued) and end with our findings from the questionnaires the participants filled out post-experiment and the user's opinions after a short interview.

5.1 Driving Data

In this section we will discuss our findings when reviewing the driving data obtained after the users took back control from the automated system and comparing it not only between the three systems but also to the drive the participants performed before turning on the automated system, the baseline drive, to see if the difference between driving pre-automation and driving post-automation found in most studies in the literature review is also found in our study.

5.1.1 Baseline comparison

Starting precisely with our comparisons to the baseline, what we discovered in the literature review also happened in our study: when comparing the two periods of driving (pre and post automation) for each of the systems tested there was a lot of significant statistical differences to be found ($p\ value \leq 0.05$). The differences found in the average braking input between the two driving stints were to be expected since participants had to use the brake in order to decelerate the car and take the exit safely, while in the baseline drive most participants didn't use the brake, or barely used it, thanks to the period the participants had to get used to the vehicle's dynamics before testing any of the systems and the fact they didn't face many sharp turns or traffic in the baseline drive.

The difference in terms of the standard deviation of absolute lane position and standard deviation of steering angle was also to be expected, according to the literature; after a period of not driving, in this case due to the automation being on, when drivers regain control of the car they tend to go through a small period of readjusting to the vehicle's dynamics, and in our study we found this happened, for all of the systems tested [54, 7, 47, 11]. The AR system was the only of the three systems who only presented a significant statistical difference in the absolute lane position inbetween the manoeuvres the participant had to perform, as we can see in the previous chapter's section 4.2.2.C, suggesting maybe the driver was more consistent than with the other two system; the HUD Warning system was also the only one who showed a significant difference in the standard deviation of speed the vehicle carried, meaning with this system participants were slightly less predictable, and the one of the worst things a driver can be on the road is unpredictable, i.e. having a low control level [10], so it's possible the HUD Warning system would need some adjustments to eliminate this unpredictability from the driver's behaviour.

5.1.2 Comparison between systems

Moving on to the comparison between the driving the participants did after they took over when being alerted by the TOR emitted by each of the three systems, it was hard to find differences in the driving data of the three systems. Because of the higher time participants took to make the switch from the left lane to the right lane when using the AR system we found a significant statistical difference in the average absolute lane position in the first 25 seconds and, consequently, in the first 30 seconds, due to participants making the switch, on average, in that 5 second period between 20 and 25 seconds (average time to make the switch from the left lane to the right lane was 22.005 seconds). Due to this lack of differences between the driving participants did post-takeover using each of the three systems we believe **Hypothesis 2** is verified, neither of the two new takeover systems led to a decrease in takeover quality, measured mainly by the standard deviation of steering angle and absolute lane position, when compared to the industry standard (IS) system.

Since the participants made the switch later with the AR system than with the other two systems that explains the increase in absolute lane position since to make the switch drivers need to depart from the middle of the lane (when absolute lane position equals 0) and then readjust after crossing to the right lane. We believe this increase in time to make said switch could be due to the increased amount of information for the user to take in before making the switch to the right lane, whereas with the other systems most, if not all the information was given to the user before he took over from the automated system. With more information available to them it's expected they would take more time to consume said information, in order to better and more safely takeover, and thus take longer to make the manoeuvre with the AR system.

As we can see in the previous chapter 4, the three systems were indistinguishable from one another from a statistical point of view, the main difference found was in the time taken to perform each event, as mentioned previously. The HUD Warning system led to an increased time for the participant to place both hands on the wheel, which was expected since the participant needed a hand to interact with the center console; and this increase in time also led to the takeover moment (when the participant turned off the automation) to occur slightly later than in the other two systems. With none of the systems the participants really used close to the 30 seconds available to takeover, averaging around 10 seconds to takeover from the automated system, which lines up with what we found in the literature [53], but we believe this was due to inexperience in this scenario, since none of the participants had much experience with automated systems in vehicles.

The difference in time between making the switch from the left lane to the right lane and moment when the participants took over, even though it was not statistically significant, was considerable, with the AR system making participants take 5 more seconds after taking over to make the switch to the right lane; this is might be due to the fact the AR system was the only one that explicitly told the participant the safety of the manoeuvre and thus participants took longer to evaluate the situation and make sure the manoeuvre was completely safe to perform. Due to this increase in time participants took to make the first switch when using the AR system the subsequent difference between the average time taken to switch and the time before the first brake input was shorter for the AR system than the other two systems.

Also should be mentioned that the reason for the big difference, for all three systems, between the time taken before the first brake input and the time before the switch out of the highway was due to a difference in approaches across all participants; sometimes participants would opt to brake and slot in behind the car on their right, with the moment of first brake input coming much earlier than the average time observable in the figure 4.1, while others opted to accelerate and overtake the car, only braking to slow down before the exit, with the moment of first brake input coming much later. This difference in approaches is something worth investigating in the future: if the real reason for this difference in approaches was simply inexperience in this type of situation from the participants or an effect from the type of TOR emitted to the participant.

Given the data we obtained and the points explained above, we don't believe **Hypothesis 5** was verified since little difference was found between the driving done post-takeover for the AR system and HUD Warning system and we don't think the fact users took longer to switch from the left lane to the right lane when using the AR system improved the takeover quality enough when compared to the HUD Warning system.

5.2 Driver Behaviour

In this section we'll discuss how the drivers behaved when they needed to regain the control of the car, any anomalies found and if the gaze data indicates any trend in how the users reacted to the takeover request (TOR).

Upon the TOR being emitted, most participants behaved as expected, and wanted: they checked their surroundings to ensure they understood how the situation had changed since turning the automation on and diverting their attention from the driving. One participant though was more cautious than others and didn't fully divert their attention away from the road during the period while the automation was on; which is to be expected in the real world, especially during the early stages of SAE level 3 and 4 automation where users might not want to put that much trust into a self-driving vehicle.

Only one of the participants missed the exit they were supposed to take, testing the IS system, but since this was a one time occurrence we believe it was more of an error from the driver rather than an indication that the IS system was the cause of it. Another participant didn't take the exit correctly with the IS system but, since it was a one off, just like the other participant missing the exit, we believe it was just driver error again. Another one of the participants also didn't take it correctly; they didn't slow down enough and went off the road in the first two systems they tested but learned how to make the exit safely by the time he/she/them tested the final system. We believe these errors were simply driver error, possibly due to the small amount of time to get used to the situation and vehicle dynamics, even though participants were given a period to get used to the simulation before starting the experiments. It was to be expected that some participants would find it harder to adjust; a possible solution to eliminate this lack of experience would be a more longitudinal study, where participants came back to perform the experiment, or a variation of it, a few more days to understand how they adjusted their behaviour with the experience obtained.

5.2.1 Gaze data

The gaze data confirms users were cautious when taking over, checking all of the mirrors, even the left sided one, which wasn't needed in this situation since the two manoeuvres the participant had to make were both to the right side of the vehicle, as was to be expected according to White [11]. As expected, when users were testing the HUD Warning system was when we observed more gazes, on average, towards said HUD; interestingly though, when participants tested the AR system, on average they gazed more towards the the arrows pointing towards the exit (Exit Indicator) than they did towards the HUD when the participants tested the HUD Warning system. This may be due to the fact they found the arrows more useful than the HUD Warning shown to them due to the fact it visually gave them a confirmation about which exit to take (something not present in the HUD Warning system), which was true given the responses participants gave in the short interviews that ended the study, which we'll talk about later in this chapter.

Another two expected findings was the facts participants gazed less on average towards the center console when testing the AR system, which makes sense since nothing appeared in said center console, and gazed slightly more towards the right window, presumably to check the state of the closest vehicle outline. On the other hand, the overlays used on the AR system didn't really affect the amount of gazes or the participant's dwell time on the targets, neither for the mirrors or the exit signs.

In terms of the glance duration towards the individual targets the participants didn't glance too long at targets off the road with either of the three systems, which is a positive from a safety point of view. The glances towards the exit arrows in the AR system and the exit signs being longer than those towards the other targets is not a reason of alarm since the participant's gaze wasn't fully off the road; and even the longer glances on average didn't come close to the two seconds associated with increase crash risk

[42].

The estimated time participants spent with their eyes on the road also didn't show anything out of the ordinary, no difference between the three systems but most importantly, the users didn't spend too much time with the eyes off the road, as we can see in figure 4.36.

5.3 User opinion

In this final section of this chapter we will discuss our findings on the user's response to the NASA-TLX form, the SART form, our short form and what they stated in the short interview conducted that ended each experiment.

In terms of the NASA-TLX no system distinguished itself any of the 2 others, as shown in 4.37; the closest to a statistical significant difference was in the frustration reported by the participants, with the AR system being the one with which participants reported the least frustration. In terms of overall workload the AR system had the smaller ”box”, meaning the difference between the upper and lower quartile was the smallest of the three systems, but also had the highest maximum of the three, indicating that it may not be suited to all users. However, for the mental demand aspect of the Task Load Index, we did observe that the AR system had a higher median than the other two systems, possibly indicating the participants had more to think/consider with the AR system. Based on these findings we can say we didn't find **Hypothesis 3** to be true, participants did not report lower mental workload while using either of the two proposed systems compared to the IS system.

As mentioned in the previous chapter, for the Situation Awareness Rating Technique (SART) no significant statistical difference was found for the participant's responses, neither for the individual parameters or the overall situation awareness (SA). As was expected the AR system was ranked, on average, as the system with the most amount of information; it was also rated highest in terms of Concentration of Attention of the three systems and interestingly, the lowest in terms of Complexity of the situation while we can also observe that the IS system had the lowest reported Instability of the situation.

The HUD Warning system had a slightly higher reported Attentional Demand than the other two systems; while on the other hand, the AR system had a slightly higher average value of Attentional Supply. Even though there was no significant statistical difference, the HUD Warning system lacks a bit behind the other two systems in terms of Overall SA, something worth investigating in the future. However, as pointed out, there was no significant statistical difference in terms of overall SA so **Hypothesis 4** was also not verified since the two proposed systems did not lead to a higher reported SA compared to the IS system, on the contrary, the HUD Warning system actually led to slightly lower SA compared to the other two systems.

Confirming the observed with the SART, the participants reported the AR system as being the one with the most amount of information out of the three. Interestingly, participants rated the HUD Warning system as the most intrusive of the three, and rated the IS as the system they felt the most safe regaining control with. However, as we can see in the figure 4.40, all these differences mentioned were all very small and nothing statistically significant, but these are observations that could be explored in the future.

5.3.1 Driver's Interview Answers

The first point we wanted to clarify with the participants was which one of the systems the participants preferred of the three: 4 of the participants preferred the industry standard (IS) system, 3 of the participants preferred the heads-up display (HUD) Warning system and the other 5 preferred the augmented reality (AR) system; no real general preference from the participants for one of the systems. The main advantage of the IS system pointed out by the participants was its simplicity, one of the participants said they preferred the system ”because it was simple and safe”.

The most criticized one was the HUD Warning system, with the main criticism being the complexity of it, mainly the fact the participant had to let go of the tablet to interact with the center console, possibly because the participants weren't really used to the virtual reality (VR) controls; but they did like the the objective instruction of ”You need to take the next exit” compared to looking at GPS information provided in the center console in the IS system; one of the participants suggested combining the AR and HUD Warning systems since in the HUD Warning system the warning is placed right in front of the driver, in the HUD, as the driver may not be looking at the tablet and thus miss the visual warning.

The main benefit of the AR system pointed out by the participants was the outline to the right of the participant's vehicle, a participant stated ”the outline aided in performing the manoeuvre”. However, the participants who didn't prefer the AR system felt the overlays didn't help and felt overwhelmed by the amount of information available to them, which could explain the increases in time taken by the participants not only to takeover from the automated system but also to make the manoeuvre from the left lane to the right lane; one of the participants suggested getting rid of outline and moving the color coding of it, that indicated how safe the manoeuvre would be (which participants liked), to the overlays on the mirrors, thus reducing the amount of information. Another participant suggested moving the outline slightly forward, to make it visible through the windshield, so that the driver wouldn't need to turn the head towards the right window in order to understand if it was safe to make the manoeuvre or not.

These suggestions given by the participants possibly point out that more users would be accepting, or maybe even prefer the AR system with some adjustments, and the same could be said for the HUD Warning system, possibly taking away the aspect of having to interact with the center console and having the information scroll by automatically. Most participants who preferred the AR system also indicated the arrows indicating the exit to take, based on the Mercedes prototype [68], were one of the major benefits of this approach, which, pairing with the notes some participants gave on the HUD Warning system suggests, again, that, when it comes to simply making an exit of the highway, participants prefer a more objective symbolization compared to viewing GPS data.

Taking into account the driving data, the driving behaviours (evaluated through collected gaze data) and the user responses, we did not find **Hypothesis 1** to be true because participants were fans of the simplicity of the IS system and the driving data didn't show much difference between the three systems. On the other hand, user preference favoured the AR system compared to the HUD Warning system so it's possible, with more experience in these situations that takeover quality could improve and **Hypothesis 5** could be proven, that, as pointed out in section 5.1.2, was not verified with this experiment.

In the next and final section we'll summarize our findings and explain how we believe our study can, and should, affect takeover system design in AVs.

6

Conclusion

Automation in vehicles will become more and more prevalent as time goes on, with multiple companies designing level 3 autonomous cars, and with electric vehicles becoming more and more common an increase in presence of automation in vehicles will follow so it is important that appropriate research is done beforehand to ensure the drivers interact appropriately with the systems and know the system's shortcomings [69, 34, 3, 1, 70].

As mentioned in the literature review a good amount of work has already been done but more focused towards the resumption of control in urgent situations in order to avoid crashes but it's reasonable to assume that, as these automated systems improve, the driver will have more time available to resume control of the vehicle so it's important to understand how he/she/them will behave when more time is available [54, 71, 6, 56].

Another aspect that has been studied by the community is new ways of presenting a takeover request (TOR) to the driver and how these affect the driver, from how long they take before resuming control to their driving after resuming control [72, 6, 51, 11]. Our objective was studying these two aspects: how drivers would react when given more time to takeover, and the consequent driving after they took over; and how different systems' TOR affect, either positively or negatively, the flow of actions the driver undertakes before and after regaining control of the vehicle.

We believe that we found some interesting points that can help designers of the vehicle's TOR to design systems that more adequately meet the user's needs, especially considering that a period where the automated system is on for a prolonged amount of time negatively affects the user's situation awareness (SA) and as these automated systems become better and better, they will takeover for longer and longer.

We found that the participant's preference between the three systems mainly came down to user preference, with the HUD Warning system generally being the least preferred of the three. We confirmed what numerous other papers had already shown: after a period of inactivity driver's tend to go through a readjusting period where they get reacquainted with the vehicle dynamics and thus are less consistent with their driving after taking over when comparing with driving done before handing off control, the commonly referred to out-of-the-loop problem [41, 13, 47, 55, 11].

We found some interesting points that deserved to be explored in the future in terms of the reported workload: participants found the AR system to be slightly less frustrating than the other two systems they tested, something that may be improved upon with adjustments to the AR system pointed out in the previous chapter 5.

When comparing the driving done post-takeover for each system it was very similar, the main difference found was the fact participants took longer to regain control and to switch from the left lane to the right lane, in our study's case when using the AR systems, indicating that if the information is available to the user, they will use it and interpret it before committing to a decision. On the other hand, the simplicity of the current industry standard used for TOR was praised for its by participants.

Although we found some points worth expanding upon with further experiments, it's worth reinforcing the lack of statistical differences found in the data we collected, possibly indicating that from a driving standpoint not much difference will be found between different ways to alert the driver to regain driving control. On the other hand, we believe the main driving force in the design of a takeover system should be the user experience and preference, since it would be them using and being alerted by it on a regular basis, and any irregularities that these laboratory studies, like ours, find in the driving post takeover may be reduced with experiencing these situations more and more, on a daily basis possibly even, although we're still quite away from these system being available for everyday use. And in our study the participant's preference was clear: they prefer clear and objective information (with some even pointing out that while the AR system had the most information of the three, maybe it could be reduced and the information quality could improve) and they don't think it's helpful having to physically interact with the system in order to obtain more information, since the driver's hands should be on the wheel while driving, and that was the one of the first things they did after disengaging with the NDRT, putting their hands on the steering wheel.

We know there is still a lot of investigation around these themes to be made, and we believe should be made, especially when it comes to how the user's experience affects their behaviour since vehicles, normally, are used daily; and there are still points discussed in the previous chapter 5 that may or may not be confirmed with further testing. However, we believe we've helped in understanding a bit more how users could react in these sorts of situations and how vehicle companies can help, not only the driver in taking over with the way they opt to alert and inform the driver upon a TOR, but also the other drivers around them, since a safer transfer of control would be beneficiary to the driver of the vehicle itself and, by consequent, the other drivers around them; because in an ideal world, albeit still very far in the future, when a driver handed control to an automated system and then regained at another point, the drivers around them wouldn't even notice the switch.

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A

Driving Data Statistical Results

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Mean Acceleration	0.65940	0.52449
	Mean Braking	0.46565	0.63219
	Mean Absolute Lane Position	2.24474	0.12346
	Mean Speed	0.37188	0.69257
Before Right Lane Switch	Mean Acceleration	0.54685	0.58393
	Mean Braking	0.35853	0.70139
	Mean Absolute Lane Position	2.43143	0.10350
	Mean Speed	0.06964	0.93287
Inbetween Switches	Mean Acceleration	2.69633	0.08378
	Mean Braking	1.31772	0.28280
	Mean Absolute Lane Position	1.07562	0.35388
	Mean Speed	2.36814	0.11094
First 5 seconds	Mean Acceleration	0.09633	0.90842
	Mean Braking	0.53265	0.59201
	Mean Absolute Lane Position	1.27301	0.29338
	Mean Speed	0.33497	0.71776
First 10 seconds	Mean Acceleration	0.70205	0.50282
	Mean Braking	0.25153	0.77908
	Mean Absolute Lane Position	0.10500	0.90062
	Mean Speed	0.02864	0.97179
First 15 seconds	Mean Acceleration	0.61686	0.54574
	Mean Braking	0.18516	0.83183
	Mean Absolute Lane Position	0.65238	0.52739
	Mean Speed	0.11158	0.89476
First 20 seconds	Mean Acceleration	0.81069	0.45321
	Mean Braking	0.00005	0.99995
	Mean Absolute Lane Position	1.30374	0.28513
	Mean Speed	0.09200	0.91234
First 25 seconds	Mean Acceleration	0.56241	0.57520
	Mean Braking	0.01555	0.98458
	Mean Absolute Lane Position	3.75707	0.03388
	Mean Speed	0.10979	0.89635
First 30 seconds	Mean Acceleration	0.93252	0.40368
	Mean Braking	0.08003	0.92326
	Mean Absolute Lane Position	4.38590	0.02046
	Mean Speed	0.18966	0.82814
Full 60 seconds	Mean Acceleration	1.41818	0.25653
	Mean Braking	0.12997	0.87857
	Mean Absolute Lane Position	2.06723	0.14261
	Mean Speed	1.29829	0.28658

Table A.1: Statistical results for the comparison between approaches' mean values.

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Std. Deviation Acceleration	0.40711	0.66919
	Std. Deviation Braking	0.94433	0.40020
	Std. Deviation Steering Angle	1.73281	0.19402
	Std. Deviation Absolute Lane Position	2.43075	0.10511
	Std. Deviation Speed	0.89689	0.41849
Before Right Lane Switch	Std. Deviation Acceleration	0.43850	0.64871
	Std. Deviation Braking	0.39662	0.67575
	Std. Deviation Steering Angle	2.91929	0.06802
	Std. Deviation Absolute Lane Position	1.08192	0.35066
	Std. Deviation Speed	2.80971	0.07468
Inbetween Switches	Std. Deviation Acceleration	0.49665	0.61348
	Std. Deviation Braking	2.04519	0.14701
	Std. Deviation Steering Angle	0.05000	0.95131
	Std. Deviation Absolute Lane Position	2.03730	0.14803
	Std. Deviation Speed	0.29117	0.74948
First 5 seconds	Std. Deviation Acceleration	0.03824	0.96252
	Std. Deviation Braking	0.54455	0.58522
	Std. Deviation Steering Angle	0.06356	0.93853
	Std. Deviation Absolute Lane Position	0.33191	0.71992
	Std. Deviation Speed	0.86662	0.42972
First 10 seconds	Std. Deviation Acceleration	0.00466	0.99535
	Std. Deviation Braking	0.06524	0.93696
	Std. Deviation Steering Angle	0.22846	0.79701
	Std. Deviation Absolute Lane Position	0.10239	0.90297
	Std. Deviation Speed	1.59505	0.21815
First 15 seconds	Std. Deviation Acceleration	0.07276	0.92997
	Std. Deviation Braking	0.08999	0.91416
	Std. Deviation Steering Angle	0.51450	0.60252
	Std. Deviation Absolute Lane Position	0.08193	0.92152
	Std. Deviation Speed	1.06635	0.35583
First 20 seconds	Std. Deviation Acceleration	0.04135	0.95954
	Std. Deviation Braking	0.00633	0.99369
	Std. Deviation Steering Angle	0.81026	0.45340
	Std. Deviation Absolute Lane Position	0.23991	0.78806
	Std. Deviation Speed	2.60499	0.08904
First 25 seconds	Std. Deviation Acceleration	0.38038	0.68656
	Std. Deviation Braking	0.01446	0.98565
	Std. Deviation Steering Angle	0.71341	0.49737
	Std. Deviation Absolute Lane Position	1.75075	0.18939
	Std. Deviation Speed	1.55039	0.22723
First 30 seconds	Std. Deviation Acceleration	0.87571	0.42602
	Std. Deviation Braking	0.08977	0.91436
	Std. Deviation Steering Angle	0.55674	0.57836
	Std. Deviation Absolute Lane Position	2.38428	0.10785
	Std. Deviation Speed	0.76051	0.47545
Full 60 seconds	Std. Deviation Acceleration	1.87978	0.16860
	Std. Deviation Braking	0.69470	0.50638
	Std. Deviation Steering Angle	0.87298	0.42713
	Std. Deviation Absolute Lane Position	6.91177	0.00311
	Std. Deviation Speed	0.88312	0.42304

Table A.2: Statistical results for the comparison between approaches' standard deviations.

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Mean Acceleration	2.77833	0.11113
	Mean Braking	8.58637	0.00828
	Mean Absolute Lane Position	6.76824	0.01707
	Mean Speed	0.08319	0.77599
Before Right Lane Switch	Mean Acceleration	0.74474	0.39746
	Mean Braking	0.71326	0.40745
	Mean Absolute Lane Position	21.03193	0.00014
	Mean Speed	0.00844	0.92761
Inbetween Switches	Mean Acceleration	1.22989	0.28059
	Mean Braking	10.20608	0.00455
	Mean Absolute Lane Position	4.02459	0.05856
	Mean Speed	0.08472	0.77400

Table A.3: Statistical results for the comparison between baseline and Industry Standard mean values.

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Std. Deviation Acceleration	2.85794	0.10645
	Std. Deviation Braking	11.85634	0.00257
	Std. Deviation Steering Angle	1.27782	0.27168
	Std. Deviation Absolute Lane Position	20.05030	0.00023
	Std. Deviation Speed	0.85397	0.36645
Before Right Lane Switch	Std. Deviation Acceleration	0.23120	0.63539
	Std. Deviation Braking	0.19469	0.66334
	Std. Deviation Steering Angle	4.57409	0.04381
	Std. Deviation Absolute Lane Position	35.78570	0.00001
	Std. Deviation Speed	6.73340	0.01653
Inbetween Switches	Std. Deviation Acceleration	1.77514	0.19773
	Std. Deviation Braking	13.93215	0.00131
	Std. Deviation Steering Angle	2.44546	0.13355
	Std. Deviation Absolute Lane Position	12.97625	0.00178
	Std. Deviation Speed	0.67563	0.42079

Table A.4: Statistical results for the comparison between baseline and Industry Standard standard deviations.

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Mean Acceleration	17.69324	0.00036
	Mean Braking	9.83755	0.00480
	Mean Absolute Lane Position	1.12198	0.30099
	Mean Speed	3.21667	0.08665
Before Right Lane Switch	Mean Acceleration	0.43125	0.51819
	Mean Braking	1.40125	0.24915
	Mean Absolute Lane Position	8.19637	0.00904
	Mean Speed	0.11109	0.74206
Inbetween Switches	Mean Acceleration	18.97202	0.00025
	Mean Braking	10.11966	0.00432
	Mean Absolute Lane Position	0.00003	0.99569
	Mean Speed	5.98608	0.02287

Table A.5: Statistical results for the comparison between baseline and HUD Warning mean values.

Data Range	**Measure**	***Q* value**	***p* value**
Before Exit Lane Switch	Std. Deviation Acceleration	3.63653	0.06967
	Std. Deviation Braking	11.29854	0.00282
	Std. Deviation Steering Angle	1.63226	0.21471
	Std. Deviation Absolute Lane Position	16.19016	0.00057
	Std. Deviation Speed	7.54388	0.01178
Before Right Lane Switch	Std. Deviation Acceleration	0.13923	0.71262
	Std. Deviation Braking	0.65874	0.42570
	Std. Deviation Steering Angle	0.41213	0.52752
	Std. Deviation Absolute Lane Position	28.60791	0.00002
	Std. Deviation Speed	0.11898	0.73342
Inbetween Switches	Std. Deviation Acceleration	0.85559	0.36501
	Std. Deviation Braking	12.08604	0.00214
	Std. Deviation Steering Angle	3.73998	0.06609
	Std. Deviation Absolute Lane Position	10.13170	0.00430
	Std. Deviation Speed	6.49000	0.01835

Table A.6: Statistical results for the comparison between baseline and HUD Warning standard deviations.

Data Range	**Measure**	***Q* value**	***p* value**
Before Exit Lane Switch	Mean Acceleration	1.58740	0.22090
	Mean Braking	4.50296	0.04534
	Mean Absolute Lane Position	15.82504	0.00064
	Mean Speed	0.10012	0.75467
Before Right Lane Switch	Mean Acceleration	0.24011	0.62898
	Mean Braking	1.53001	0.22915
	Mean Absolute Lane Position	41.92228	0.00000
	Mean Speed	0.16228	0.69095
Inbetween Switches	Mean Acceleration	8.76423	0.00723
	Mean Braking	3.91830	0.06041
	Mean Absolute Lane Position	5.36092	0.03031
	Mean Speed	0.27117	0.60775

Table A.7: Statistical results for the comparison between baseline and AR System mean values.

Data Range	Measure	*Q* value	*p* value
Before Exit Lane Switch	Std. Deviation Acceleration	6.76071	0.01634
	Std. Deviation Braking	3.99204	0.05823
	Std. Deviation Steering Angle	0.00059	0.98077
	Std. Deviation Absolute Lane Position	39.57842	0.00000
	Std. Deviation Speed	2.24604	0.14817
Before Right Lane Switch	Std. Deviation Acceleration	0.22096	0.64294
	Std. Deviation Braking	1.41895	0.24627
	Std. Deviation Steering Angle	0.35446	0.55768
	Std. Deviation Absolute Lane Position	38.93110	0.00000
	Std. Deviation Speed	0.01153	0.91546
Inbetween Switches	Std. Deviation Acceleration	2.01142	0.17013
	Std. Deviation Braking	3.66328	0.06872
	Std. Deviation Steering Angle	4.03187	0.05708
	Std. Deviation Absolute Lane Position	22.14066	0.00011
	Std. Deviation Speed	0.01910	0.89134

Table A.8: Statistical results for the comparison between baseline and AR System standard deviations.

B

Driver Behaviour and Forms Statistical Results

Target	Measure	Q value	p value
Left Window	Amount Of Gazes	0.36542	0.69668
	Total Dwell Time	0.91373	0.41093
	Mean Glance Duration	0.17801	0.83773
Left Mirror	Amount Of Gazes	0.61930	0.54446
	Total Dwell Time	0.29371	0.74742
	Mean Glance Duration	0.52440	0.59676
HUD	Amount Of Gazes	16.16522	0.00001
	Total Dwell Time	5.28609	0.01020
	Mean Glance Duration	0.84860	0.43714
Instrument Cluster	Amount Of Gazes	2.58862	0.09030
	Total Dwell Time	1.83442	0.17562
	Mean Glance Duration	0.11268	0.89378
Center Console	Amount Of Gazes	5.36809	0.00959
	Total Dwell Time	3.84839	0.03146
	Mean Glance Duration	0.53528	0.59050
Rearview Mirror	Amount Of Gazes	0.08900	0.91506
	Total Dwell Time	0.26738	0.76702
	Mean Glance Duration	1.79119	0.18260
Right Mirror	Amount Of Gazes	4.05478	0.02663
	Total Dwell Time	0.96837	0.39023
	Mean Glance Duration	0.99770	0.37958
Right Window	Amount Of Gazes	3.92074	0.02967
	Total Dwell Time	2.61701	0.08812
	Mean Glance Duration	0.55169	0.58120
Tablet	Amount Of Gazes	0.71937	0.49454
	Total Dwell Time	0.05181	0.94958
	Mean Glance Duration	1.62965	0.21138
Exit Sign 13 Soon	Amount Of Gazes	0.81148	0.45287
	Total Dwell Time	0.05616	0.94548
	Mean Glance Duration	2.41100	0.10537
Exit Sign 13 500m	Amount Of Gazes	0.69730	0.50512
	Total Dwell Time	0.44186	0.64659
	Mean Glance Duration	0.85303	0.43530
Total	Amount Of Gazes	0.82360	0.44767
	Total Dwell Time	0.30797	0.73703
	Mean Glance Duration	0.04715	0.95401

Table B.1: Statistical results for the comparison between approaches' driver eye gaze data towards individual targets.

Target Group	Measure	Q value	p value
Mirrors	Amount Of Gazes	0.10011	0.90501
	Total Dwell Time	0.40315	0.67146
	Mean Glance Duration	1.99507	0.15208
Windows	Amount Of Gazes	0.97874	0.38643
	Total Dwell Time	1.69245	0.19966
	Mean Glance Duration	0.41277	0.66518
Interior	Amount Of Gazes	3.91089	0.02991
	Total Dwell Time	3.64548	0.03712
	Mean Glance Duration	0.64618	0.53055
Signs	Amount Of Gazes	0.75737	0.47687
	Total Dwell Time	0.05973	0.94212
	Mean Glance Duration	0.27287	0.76289
Digital	Amount Of Gazes	6.29994	0.00481
	Total Dwell Time	10.45631	0.00030
	Mean Glance Duration	8.22116	0.00127
Road/Others	Amount Of Gazes	NaN	NaN
	Total Dwell Time	0.98293	0.38490
	Mean Glance Duration	NaN	NaN
Total	Amount Of Gazes	0.43698	0.64967
	Total Dwell Time	0.95179	0.39639
	Mean Glance Duration	0.10847	0.89752

Table B.2: Statistical results for the comparison between approaches' driver eye gaze data towards the groups of targets.

Measure	Q value	p value
Mental Demand	0.54545	0.76130
Physical Demand	0.00000	1.00000
Temporal Demand	0.17391	0.91672
Performance	0.61905	0.73380
Effort	1.19048	0.55143
Frustration	5.17241	0.07531
Overall Workload	1.31915	0.51707

Table B.3: Statistical results for the NASA-TLX answers.

Measure	**Q value**	**p value**
Instability of Situation	4.22222	0.12110
Complexity of Situation	0.82759	0.66114
Variability of Situation	2.80000	0.24660
Arousal	1.58824	0.45198
Concentration of Attention	1.58824	0.45198
Division of Attention	1.56250	0.45783
Spare Mental Capacity	0.29630	0.86230
Information Quantity	3.30769	0.19131
Familiarity with Situation	0.25000	0.88250
Attentional Demand	2.26316	0.32252
Attentional Supply	0.60465	0.73910
Understanding	0.83871	0.65747
Overall Situation Awareness	2.16667	0.33847

Table B.4: Statistical results for the SART answers.

Measure	**Q value**	**p value**
Amount of Information	0.50000	0.77880
Intrusiveness	1.60000	0.44933
Safety	0.51852	0.77162

Table B.5: Statistical results for the short form answers.