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Developing an Enriched Multi–source Data Collection Framework for Driving Behavior Modeling

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Abstract

Road crashes result each year in a loss of millions of lives across the world. Understanding factors impacting these crashes is therefore crucial to reduce and even prevent road fatalities, and is in line with the European Union's long-term vision to move as close as possible to zero fatalities, also known as "Vision Zero". Previous research has helped group crash factors between vehicle, environment, and driver-related factors, the latter often thought to be the leading cause behind road crashes. Better understanding the way people drive would be key in predicting, but also mitigating road accidents. As crashes are rare events, surrogate safety measures can instead be evaluated, to assess safety performance. Still, such assessments require sufficient data collection, based on different conditions, considering individual characteristics, and depending on the research questions of interest. Conducting studies focusing on the collection of driving behavior data has therefore become of high interest.

Owing to technological advances, in-vehicle sensors are becoming more accessible, and can provide driving-related data with a high level of accuracy. Studies usually deploy such sensors and include driving simulator studies, in which specific risk scenarios are investigated, that might not be feasible in real road conditions, and more recently naturalistic driving studies (NDS), which tend collect data in a less obtrusive manner, and for longer study periods; yet they are more challenging to administer. Data collected within these studies come from various sources, including vehicle data, questionnaire data, but also a variety of devices, including visual tracking, wearables collecting biometric data, etc. However, such data collection is often associated with major challenges, including the heterogeneity of data, but also its size, and nature, i.e., sensitive personal data. It becomes therefore imperative to develop a framework that tackles such challenges and that provides the necessary steps from data collection to behavioral modeling.

This dissertation contributes to the field of driving behavior modeling by developing an enriched multi-source data collection framework for driving behavior modeling. A data-knowledge-information cycle is first developed, after an extensive literature review of data collection studies, including both analytics and fusion components. Further, a review of previous NDS studies has led to the development of standard protocols for data handling, including protocols for data collection, preparation, storage, and legal and ethical considerations. Based on such learnings, a multi-modal cross-country case study in which these protocols are applied is demonstrated, including both driving simulators and NDS. After presenting the data collection framework for the entire study, this dissertation collects data within a car driving simulator experiment organized in Germany, to investigate risk factors of vulnerable road user collisions and tailgating, under different conditions, such as distraction and the presence of an advanced warning-monitoring system. The collected data for 60 participants included driving simulator data, eye tracking data, and questionnaire data.

The data has then been analyzed, using first inferential statistics, and then panel regression models. Further, the acceptance of drivers for the system experienced has been assessed and represented in terms of the renowned technology acceptance model. Results have shown that indeed the intervention systems have improved driving performance in the safety-critical events, while distraction on the other hand has deteriorated it, and that visual tracking can provide meaningful insights for distraction assessment. Moreover, drivers‘ demographics and perceptions have also proved to be significant in the explanatory driving performance models. The advanced warning-monitoring system were highly accepted by participants, with perceived ease of use and perceived usefulness identified as key factors in representing it. In assessing the transferability of this model across modes, similar findings were shared with other road modes, notably with truck drivers. The different study findings have paved the way to the successful development of a data collection framework, allowing the extraction of meaningful information, that can be also transferable. In particular, the findings of this study will allow the further refinement of the presented technology, but will also provide useful insights on the possibility to transfer knowledge, across modes, and even from the simulator environment to the real-road experiments.

Zusammenfassung

Durch Verkehrsunfälle verlieren jedes Jahr Millionen von Menschen auf der ganzen Welt ihr Leben. Deshalb ist das Verständnis der Faktoren, die sich auf diese Unfälle auswirken, von entscheidender Bedeutung, um die Zahl der Verkehrstoten zu verringern und sogar zu verhindern. Dies steht im Einklang mit der langfristigen Vision der Europäischen Union, die darauf abzielt, die Zahl der Verkehrstoten so gering wie möglich zu halten, auch bekannt als "Vision Zero". Frühere Studien haben dazu beigetragen, die Unfallfaktoren in fahrzeug-, umwelt- und fahrerbezogene Faktoren aufzuteilen, wobei die letzteren häufig als Hauptursache für Verkehrsunfälle angesehen werden. Ein besseres Verständnis des Fahrverhaltens der Menschen wäre der Schlüssel zur Prognose von Verkehrsunfällen, aber auch zu deren Minderung. Da Unfälle seltene Ereignisse sind, können stattdessen Ersatz-Sicherheitsmaßnahmen bewertet werden, um die Sicherheitsleistung zu beurteilen. Solche Bewertungen erfordern jedoch eine ausreichende Datenerfassung unter verschiedenen Bedingungen, unter Berücksichtigung individueller Merkmale und in Abhängigkeit von den Forschungsfragen, die von Interesse sind. Die Durchführung von Studien, die sich auf die Erfassung von Fahrverhaltensdaten konzentrieren, ist daher von großem Interesse.

Durch den technologischen Fortschritt werden Sensoren im Fahrzeug immer leichter zugänglich und können fahrbezogene Daten mit einem hohen Genauigkeitsgrad liefern. Zu den Studien, in denen solche Geräte in der Regel eingesetzt werden, gehören Fahrsimulatorstudien, in denen spezifische Risikoszenarien untersucht werden, die unter echten Straßenbedingungen möglicherweise nicht durchführbar sind, und in letzter Zeit auch naturalistische Fahrstudien (NDS), bei denen Daten in der Regel auf weniger aufdringliche Weise und über längere Untersuchungszeiträume erhoben werden, die jedoch schwieriger zu verwalten sind. Die im Rahmen dieser Studien erfassten Daten stammen aus verschiedenen Quellen, darunter Fahrzeugdaten, Fragebogendaten, aber auch eine Vielzahl von Geräten, darunter Blickerfassung, Wearables, die biometrische Daten erfassen, usw. Eine solche Datenerfassung ist jedoch oft mit großen Herausforderungen verbunden, darunter die Heterogenität der Daten, aber auch ihr Umfang und ihre Art, d. h. vertrauliche persönliche Daten. Es ist daher zwingend erforderlich, einen Framework zu entwickeln, der solche Herausforderungen angeht und die notwendigen Schritte von der Datenerhebung bis zur Verhaltensmodellierung bereitstellt.

Diese Dissertation leistet einen Beitrag zu diesem Forschungsgebiet, indem sie einen angereicherten und aus verschiedenen Quellen stammenden Framework zur Datenerfassung für die Modellierung des Fahrverhaltens entwickelt. Zunächst wird ein Daten-Wissens-Informations-Zyklus entwickelt, nachdem eine ausführliche Literaturrecherche zu Datenerhebunsstudien durchgeführt wurde, die sowohl analytische als auch fusionierende Komponenten enthalten. Darüber hinaus hat eine Analyse früherer naturalistischer Fahrstudien zur Entwicklung von Standardprotokollen für die Datenverarbeitung geführt, einschließlich Protokollen für die Da-

tenerfassung, -aufbereitung und -speicherung sowie für rechtliche und ethische Überlegungen. Basierend auf diesen Erkenntnissen wird eine multimodale, länderübergreifende Fallstudie demonstriert, in der diese Protokolle angewandt werden und die sowohl Fahrsimulatoren als auch NDS umfasst. Nach der Darstellung des Frameworks für die Datenerfassung für die gesamte Studie werden in dieser Dissertation Daten im Rahmen eines in Deutschland durchgeführten Fahrsimulatorexperiments erhoben, um die Risikofaktoren für gefährdete Verkehrsteilnehmer und das Auffahren auf den Verkehr unter verschiedenen Bedingungen, wie z. B. Ablenkung und das Anliegen eines fortschrittlichen Warnüberwachungssystems, zu untersuchen. Die für 60 Teilnehmer erfassten Daten umfassten Fahrsimulatordaten, Blickbewegungsdaten und Fragebogendaten.

Die Daten wurden zunächst mit Hilfe von Inferenzstatistiken und dann mit Panelmodellen analysiert. Darüber hinaus wurde die Akzeptanz der Fahrer für das erlebte System bewertet und in Form des bekannten Technologieakzeptanzmodells dargestellt. Ergebnisse haben gezeigt, dass die Interventionssysteme tatsächlich die Fahrleistung bei sicherheitskritischen Ereignissen verbessert haben, während die Ablenkung diese verschlechtert hat, und dass die visuelle Verfolgung aussagekräftige Erkenntnisse für die Bewertung der Ablenkung liefern kann. Darüber hinaus haben sich auch die demografischen Daten und die Wahrnehmung der Fahrer in den Erklärungsmodellen für die Fahrleistung als signifikant erwiesen. Das fortschrittliche Warn- und Überwachungssystem wurde von den Teilnehmern stark akzeptiert, wobei die wahrgenommene Benutzerfreundlichkeit und der wahrgenommene Nutzen als Schlüsselfaktoren für die Akzeptanz des Systems genannt wurden. Bei der Bewertung der Übertragbarkeit dieses Modells auf andere Verkehrsträger wurden ähnliche Ergebnisse auch bei anderen Verkehrsträgern, insbesondere bei Lkw-Fahrern, festgestellt. Die verschiedenen Studienergebnisse haben den Weg für die erfolgreiche Entwicklung eines Frameworks zur Datenerfassung geebnet, das die Ermittlung aussagekräftiger Informationen ermöglicht, die auch übertragbar sind. Die Ergebnisse dieser Studie werden insbesondere die weitere Verfeinerung der vorgestellten Technologie ermöglichen, aber auch nützliche Erkenntnisse über die Möglichkeit des verkehrsträgerübergreifenden Wissenstransfers und sogar des Übertragens von der Simulatorumgebung auf reale Straßenversuche liefern.

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Glossary of Abbreviations and Acronyms

3G	Third generation (of cellular technology)
Abs.	Absolute value
ADAS	Advanced driver–assistance system
AFD	Average fixation duration
AIC	Akaike information criterion
AOI	Area of interest
API	Application programming interface
ASC	Alternative–specific constant
AV	Autonomous vehicle
BI	Behavioral intention
BIC	Bayesian information criterion
BN	Bayesian network
Brake displ.	Brake pedal displacement
CAN	Controller area network
CE	Critical event
CEP	Complex event processing
CF	CompactFlash
CFA	Confirmatory factor analysis
CSV	Comma-separated values
DAS	Data acquisition system
DPO	Data protection officer
DSS	DriveSimSolutions
E-bike	Electronic bike
ECG	Electrocardiogram
EFA	Exploratory factor analysis
FCW	Forward collision warning
FESTA	Field opErational teSt supporT Action
Gas displ.	Gas pedal displacement
GDPR	General data protection regulation
GPRS	General Packet Radio Service
GPS	Global positioning system
HTTPS	Hypertext Transfer Protocol Secure
Hz	Hertz
ICT	Information and communications technology
IIA	Independence of irrelevant alternatives

IID	Independent and identically distributed
km	Kilometer
KSS	Karolinska sleepiness scale
Lat. acc.	Lateral acceleration
Lat. pos.	Lateral position
Lat. vel.	Lateral velocity
Long. acc.	Longitudinal acceleration
Long. vel.	Longitudinal velocity
MAP	Minimum average partial
Max.	Maximum
Min.	Minimum
MNL	Multinomial logit model
NDS	Naturalistic driving study
OBD	On-board diagnostics
OLM	Ordered logit model
OLS	Ordinary least square
PB	Petabyte
PCA	Principal component analysis
Ped	Pedestrian
PEU	Perceived ease of use
POI	Points of interest
PTW	Powered two-wheeler
PU	Perceived usefulness
QR	Quick Response
SD	Standard deviation
SD (card)	Secure digital (card)
SE	Standard error
SHRP	Strategic highway research program
Steer. angle	Steering wheel angle
STZ	Safety Tolerance zone
SUV	Sports utility vehicle
Tail	Tailgating
TAM	Technology acceptance model
TB	Terabyte
TFD	Total fixaton duration
TOI	Time of interest
TTC	Time–to–collision
USB	Universal Serial Bus
VRU	Vulnerable road user
VTOL	Vertical take-off and landing
WLAN	Wireless local area network

1. Introduction

This introductory chapter of the dissertation introduces the motivation for the work (Section 1.1), followed by a state–of–the–art of driving behavior studies (Section 1.2), including risk factors and conditions (Section 1.2.1) and data collection studies (Section 1.2.2). After that, the thesis objectives are presented (Section 1.3), followed by the thesis contributions (Section 1.4), both methodological and practical. Finally, the thesis outline (Section 1.5) is presented.

1.1. Motivation

Road crashes take millions of lives across the world every year and as a result, understanding factors contributing to these crashes has been at the forefront of road safety research. These factors may arise from distinct sources of risk such as vehicle factors, environmental factors, and behavioral (driver-related) factors (Afghari et al., 2018). Among these, human factors have been shown to be the primary cause of crashes (Afghari, 2019), paving the way to modeling driving behavior. Furthermore, the last decades have witnessed unprecedented technological advances, which have had implications on different industries, including the mobility and transportation sector. Progresses in information and communications technology (ICT) have been manifested in different domains, such as automation, efficiency, etc. This provides an unparalleled opportunity to work towards eliminating road fatalities; in the European Union, this is also known as “Vision Zero".

A starting point would therefore be to better understand driving behavior, as it has been demonstrated to be a primary cause of crashes (Afghari, 2019), but also to have a better grasp on how technology can be used for the purpose of preventing, or at least reducing (the impact of) unsafe driving. One way could be for example the use of advanced systems to help drivers in their driving (advanced driver–assistance system, often abbreviated as ADAS), and warn them whenever boundaries of potential crashes are too close; a very well–known example for this is be the “Forward Collision Warning", also known as FCW.

In studying the impact of such (warning) systems on driving behavior, studies generally tend to focus on changes in behavior based on specific parameters, often neglecting to put together the different aspects that can influence behavior, including, but not limited to human factors, or different conditions drivers might be exposed to while driving. A motivation would therefore be to better understand driving behavior, but also have an approach to integrate different parameters, including individual-specific parameters, in a way to have a comprehensive and holistic view of driving behavior for different safety–critical situations.

In reaching this objective, experiments for the collection of data can be designed to help answer specific research questions. For instance, driving simulator studies could be developed to simulate the driving environment and research safety-critical scenarios that would be impossible to investigate in real road conditions. On-road experiments or driving tests can also be conducted to offer a more realistic driving environment; this includes field operational tests, where road tests are administered at specific road sections, in a rather more confined environment, and more recently through naturalistic driving studies (NDS).

It is therefore crucial to first highlight risk factors of interest, in order to later look at ways to mitigate them, after which an overview over the commonly deployed behavioral studies (above–mentioned) can help highlight the most common experiments but also data collection tools that can be used to collect the needed data to help answer the most prominent research questions. This state–of–the–art overview would help us highlight the thesis objectives, based on which the methodology and the rest of the work is developed.

The remainder of this chapter is organized as follows: Section 1.2 first presents an overview on human factors in road safety, highlighting a selection of risk factors and conditions (Section 1.2.1). Then, a survey of commonly used data collection studies is given (Section 1.2.2). Section 1.3 then defines the thesis objectives, which are directly formulated based on the gaps highlighted from the literature. Section 1.4 then formulates the contributions made in this work, which are grouped under two main categories: methodological contributions and practical contributions. Finally, an outline for the rest of the dissertation is presented (Section 1.5).

1.2. Driving behavior: state–of–the–art

Various risk factors push drivers closer to the boundaries of “unsafe" driving; on the other hand, various safety outcomes or objectives can improve driving safety, including but not limited to driver fitness, speed management, vehicle control, or adequately sharing the road with others. Moreover, some conditions can further aggravate such risk factors; for instance, fatigue and distraction are areas directly impacting driving fitness. Fortunately, specific warnings can be designed to help mitigate certain risks, such as tailgating, or VRU collisions; these are often part of existing ADAS.

1.2.1. Risk factors and conditions

A variety of risky situations exist that render driving unsafe; this includes VRU interactions, tailgating, illegal overtaking, over–speeding, but also driver mental state. Below, an overview on a few of them is given.

1. **VRU interactions/collisions** is a major road safety concern. VRUs, such as pedestrians, motor/pedal cyclists, and e-scooter riders, are more endangered in traffic, since they have no protection to safeguard them in case of collision. Accordingly, scenarios involving VRUs are often designed in driving simulator environments. Studies investigating pedestrian-vehicle crashes often trigger crossings at intersections and mid-block crossing areas (Chrysler, Ahmad, and Schwarz, 2015; Oza, Q. Wu, and Mourant, 2005), also in

combination with distraction and other conditions, such as different visibility factors or roadside environments and speed (Oza, Q. Wu, and Mourant, 2005; Chrysler, Ahmad, and Schwarz, 2015).

2. **Tailgating**, a leading cause of rear–end collisions, occurs when a driver drives too close behind another vehicle, without leaving sufficient time and space to avoid a crash. Tailgating is often provoked by traffic conditions, the behavior of other drivers, time pressure, driver impatience or anger, and is reflected in unsafe driving maneuvers. To better understand or mitigate tailgating, investigating driver aggressiveness can be of interest, which can be done for example by simulating a set of frustrating events in different conditions (Abou-Zeid, Kaysi, and Al-Naghi, 2011). Moreover, studying the impact of warnings, such as FCW, in assisting drivers in risky situations, can also be of help in mitigating tailgating (Koustanaï et al., 2012).

3. **Illegal overtaking** is another factor of interest, where control strategies and drivers' decision-making can be investigated (Gray and Regan, 2005). Moreover, traffic density (Farah, 2011; Yang et al., 2018) and geometric conditions (Farah, 2011) can be simulated to understand their impact on right and left lane changes and overtaking maneuvers.

4. **Driver mental state** is an important consideration and potential source of emerging risk, including attention, distraction, fatigue, and sleepiness, emotions and stress (S. Kaiser et al., 2020).

   a) **Distraction** refers to the driver's temporary diversion of attention from the task of safe driving to the secondary task(s) that is (are) not related to driving, which can originate from in-vehicle or external sources, engaging drivers (Amini et al., 2021): 1) visually: tasks that take drivers' eyes off the road, 2) auditorily: drivers' attention diverted by noises and sounds, 3) physically: tasks requiring drivers' to remove their hands from the steering wheel, and 4) cognitively: tasks that take drivers' focus and attention off while driving. Amongst various existing sources of distraction, mobile phone use is associated with the highest risk. Texting and driving, a form of mobile phone distraction, refers to the act of any kind of mobile phone use while driving, which can engage drivers visually, auditorily, physically, and cognitively. Drivers who text while driving are more prone to be involved in a safety-critical event (World Health Organization, 2011). However, understanding the relationship between mobile phone use and crash risk is not a trivial task, mostly as it is challenging to investigate in real road conditions; it is therefore often investigated in a confined simulator environment. Previous research estimated from between two to nine times higher crash risk for drivers engaged in mobile phone related distraction than non-distracted (Thomas A Dingus et al., 2016a; Sheila G Klauer et al., 2014; World Health Organization, 2011). Experiments designed to study distraction often "artificially" impose distractors, by creating tasks that engage drivers visually, and cognitively, while driving (Dumitru et al., 2018; Oviedo-Trespalacios et al., 2018; Choudhary and Velaga, 2019).

b) **Fatigue** is associated with monotony and can be evident following a long monotonous drive. It can be indicated by the number of hours driven, under the assumption that long and monotonous driving may induce fatigue directly, or indirectly through sleepiness. It can be investigated within a driving simulator environment, or in real conditions. Past studies have shown that participants in driving simulators are usually fatigued after 20 to 90 minutes of monotonous driving (Desai et al., 2007; Merat and A. H. Jamson, 2013; Philip et al., 2005; Rossi, Gastaldi, and Gecchele, 2011; Saxby et al., 2007; Ting et al., 2008; Chunlin Zhao et al., 2012).

1.2.2. Data collection studies

1. **Driving simulator studies** are generally popular in investigating the impact of imposed conditions on specific driving behavior indicators or parameters. A variety of driving simulators exist in the market, including static fixed based and dynamic (or moving/motion) simulators. A main advantage of conducting simulator experiments, as compared to real–road studies, is the much cheaper costs, but also the ability to investigate in a controlled environment risky situations that would not be possible to investigate otherwise.

   Driving simulator research includes studies investigating the impact on driving of different conditions, including but not limited to distracted driving (Oviedo-Trespalacios et al., 2018; Oviedo-Trespalacios et al., 2018; Choudhary and Velaga, 2019), driving under the influence of alcohol (Weiler et al., 2000; Mets et al., 2011; Vollrath and Fischer, 2017; Fares et al., 2022), drugs (Weiler et al., 2000; Fares et al., 2022), or even caffeine, often as a countermeasure to sleep deprivation (De Valck and Cluydts, 2001; Brice and Smith, 2001; Biggs et al., 2007).

   Weather conditions are also of interest and can be investigated in a driving simulator environment. Different weather situations (i.e., clear day, moderate rain, moderate rain-fog) can have varying impacts on driver workload (Billot, El Faouzi, and De Vuyst, 2009), and therefore driving behavior and safety; the worse the weather conditions, the higher the driver workload. Adverse weather conditions (i.e., rain, snow, heavy dense fog), have also been proven (within a simulator context) to worsen car-following performance (C. Chen et al., 2019).

   Beyond investigating the influence of such factors or conditions, driving simulators have been used in combination with other devices or features, such as visual tracking or even specific ADAS features, with the aim of testing the effectiveness or even acceptance of such systems. Previous studies have used ADAS in a driving simulator context in order to improve the system based on the assessed acceptance of drivers' perceptions. Hegeman et al. (2007) designed a driving simulator study to assess the acceptance of an overtaking assistant design in a driving simulator experiment. Results from this study proved that according to the performance of the overtaking maneuvers, it is possible to design a standardized overtaking assistant. Similarly, Driel, Hoedemaeker, and Arem (2007) conducted a study in order to assess congestion assistant, within a driving simulator context, based on which some system refinements were suggested.

Due to a relatively easier scenario design, as compared to real life, a previous study (Rossi, Gastaldi, Biondi, et al., 2020) tested a lateral control ADAS, which informed the drivers whether the vehicle was correctly positioned inside the lane or not, with the use of two visual and one auditory stimuli. The ADAS were tested on three different groups, with different configurations: with no exposure to the ADAS, with exposure but without instructions, with exposure and with instructions. Findings suggested that the group receiving instructions and reading the information booklet was able to improve more and faster their lateral control, which highlights the importance of instructing drivers on the warning system in improving its acceptability.

Finally, driving simulator studies are suitable to understand the impact of human factors or individual–specific differences on driving behavior, including socio–demographics, such as the impact of gender (Ridel et al., 2022), age (focusing mostly on teenage drivers such as in Miani et al. (2022), Sutherland et al. (2022), and Eren and Gauld (2022), or health status, such as diabetes (Ridel et al., 2022), Parkinson's disease (Uc, 2022), or Multiple sclerosis (Krasniuk et al., 2022). Human factors may also include social aspects such as social pressure resulting from the presence of other passengers (Ouimet et al., 2013; Sutherland et al., 2022), or styles and skills, which may also depend on cultural aspects (W. Wang et al., 2019; Miller, Chapman, and Sheppard, 2021) or personality traits (Zicat et al., 2018; Tement et al., 2022).

2. **Naturalistic driving studies** have recently gained attention as a way to collect driving data in an "natural" unobtrusive way in which participants drive as they "normally" do, without being asked to drive specific roads, or change their driving patterns. This is usually achieved by instrumenting participants' vehicles in an unobtrusive way and collecting driving data over long periods of time. With advances in technology and sensory equipment, NDS are increasing in popularity, but also in challenges. Driving for longer periods of time inevitably leads to large amounts of data, and therefore creates challenges in terms of data management, data sharing, and data handling in general.

3. **Visual tracking** can be defined as the process of monitoring eye movements to assess where an individual is gazing at and associated information like the object of interest the subject is looking at and the gaze duration (Franchak, 2020). To understand the role of eye trackers in studying driver distraction, we must first understand the eye-mind hypothesis. It states that what the eyes fixate on and what the mind processes occur simultaneously (Just and Carpenter, 1980). Cognitive processes are generally indicated by eye movements. Hence, tracking eye movements can lead to inferences on different cognitive processes occurring in the brain (Tobii Pro AB, 2020). The usage of visual tracking has evolved to become a popular mean to collect information based on driver eye movements, which can then infer distraction, and can be used both in simulator and real road conditions.

   Visual tracking allows to extract an array of eye tracking metrics. According to Papantoniou, Papadimitriou, and George Yannis (2017), fixation is the most important eye tracking parameter used to identify cognitive distraction. This was based on a synthesis of over forty driving simulator studies involving the investigation of distraction on the driving performance. A comprehensive literature review of over twenty-two visual tracking studies (Sharafi, Soh, and Guéhéneuc, 2015) revealed that eye tracking metrics used for the purpose of analysis can be divided into two main categories: the metrics based on the number of fixations (count), and those based on duration.

The former category measures gaze behaviour depending on the number of fixations on a specified area of interest (AOI). Gaze metrics based on the duration of fixations gave a measure of the time required to analyze a stimulus (Goldberg and Kotval, 1999). The most commonly used variables under this category included average fixation duration (AFD), ratio of on-target to all-target fixation time, total fixation time, average duration of relevant fixations and normalized rate of relevant fixations (Goldberg and Kotval, 1999; Bednarik and Tukiainen, 2005; Jeanmart et al., 2009; T. Busjahn, Schulte, and A. Busjahn, 2011; Sharif, Falcone, and Maletic, 2012; Bednarik, 2012; Binkley et al., 2013; Petrusel and Mendling, 2013; T. Busjahn, Bednarik, and Schulte, 2014; Ali et al., 2015). In such studies, it was imperative to study both categories because a particular area of interest may have a low count but a high duration and vice versa (Sharafi, Soh, and Guéhéneuc, 2015).

1.3. Thesis objectives

A main motivation for road safety research is to reduce and even eliminate crashes. In simple words, there is a need identify risky situations, so that we can mitigate them by introducing adequate countermeasures, such as personalized warning systems, among others. Driving behavior has been in general explained by one or more factors pertaining to the individual, the environment, and/or the vehicle. Various risk factors have been identified in previous studies (See Section 1.2.1), including but not limited to, VRU interactions, tailgating, etc., but also conditions like fatigue, distraction, adverse weather conditions. However, research has also shown that human factors are the leading cause of crashes Afghari (2019). An increasing interest therefore arises to better understand individual-specific factors, including drivers' demographics, attitudes, and perceptions, their impact on driving performance, but also driver and human response and feedback to assistance systems, which are normally designed to help mitigate driving risks. It becomes therefore crucial to design experiments that would help us obtain a better insight on driving behavior; this includes, but is not limited to driving simulator, naturalistic driving, and visual tracking studies (See Section 1.2.2). As research tends to analyze and assess the different risk factors and data collection studies separately, there is a gap in understanding these aspects together, as part of one large scale-study.

For instance, driving simulators can be used first to test the effectiveness of specific systems, before they are deployed in real road conditions. Driving simulator studies are of course cheaper and easier to conduct than naturalistic driving studies, and often allow to test safety-critical situations that would not be possible in real road conditions; however, they might lack realism or come with limitations, such as simulator sickness. On the other hand, while naturalistic driving studies are more realistic, they are much more complex and expensive to design and manage, and come with challenges, such as resulting in huge datasets, but also collecting personal and possibly sensitive data, which would need specialized handling protocols; the latter also applies to simulator studies.

There is a lack of studies combining both simulator and on-road studies, where learnings from the former can be implemented in the latter. Moreover, there is a need to develop a framework to guide the creation of useful knowledge necessary to improve our understanding of driving behavior, starting from the initial data collection stages; a holistic approach is also needed to develop the above-mentioned data handling protocols. Finally, it is essential to put together the data collected from different sources (including vehicle, environment, and driver data), which often come in different forms (time-series, questionnaires, etc.), to answer the needed research questions. Accordingly, the thesis objectives have been formulated as follows:

1. Developing a data–knowledge–information cycle for driving behavior modeling, encompassing all the necessary steps from data collection to information extraction and analysis, and possibly knowledge transfer.

2. Drafting protocols for the handling of data resulting from driving behavior, in particular naturalistic driving experiments.

3. Designing suitable experiments to study relevant research questions:
   a) Including different methods (simulator, naturalistic driving) and deploying different data collection devices (e.g., warning systems, visual tracking, etc.).
   b) Focusing on risk factors of interest (e.g., VRU interactions, tailgating, etc.).
   c) Focusing on conditions of interest (e.g., distraction), and their impact on safety-critical situations.

4. Assessing the results of collected data in terms of:
   a) Integrating the different data sources (e.g., subjective, objective, qualitative, quantitative) to model driving behavior in safety-critical situations.
   b) Assessing the impact of human factors on driving behavior (including attitudes and perceptions, but also individual-specific factors).
   c) Assessing the impact of ADAS on driving behavior.
   d) Assessing the impact of distraction on driving behavior.
   e) Assessing drivers' acceptance of warning-monitoring systems in different situations.

5. Discussing the possibility of findings transferability across modes and between simulator and naturalistic experiments.

1.4. Thesis contributions

In answering the research objectives, and closing the identified gaps, this dissertation would have various contributions, which are either methodological or practical, as follows.

1.4.1. Methodological contributions

This dissertation would first close a research gap by providing a comprehensive data–knowledge information cycle for driving behavior modeling, including the different steps from data collection, to making this data useful for analysis; this first contribution is openly available in Al Haddad and Antoniou (2022). Moreover, a protocol for the handling of this collected data is drafted in this dissertation, including protocols for data collection, preparation, storage, and legal and ethical considerations. Furthermore, a comprehensive and experimental guideline for data collection for modeling driving behavior in both a driving simulator and real–road conditions is outline, including the use of various data collection devices, including but not limited to custom–designed advanced–driving assistance system, eye tracking glasses, a driving simulator, and a variety of in–vehicle sensors. Finally, and as part of the data–information–knowledge cycle, this work provides insights on how to transfer findings from one mode to another; the latter is available in Al Haddad, Abouelela, Graham Hancox, et al. (2022).

1.4.2. Practical contributions

Practical contributions of this work are first the design of an experimental protocol for driving simulator and naturalistic driving studies for different modes, including data handling protocols for the adequate data use of personal data that results from these experiments. In particular, this dissertation contributes to the design of a driving simulator experiment, for assessing the impact of a custom–designed warning–monitoring system on various safety–critical events (namely VRU interactions and tailgating), and of distraction on such safety–critical events, including the collection of data from different sources (notably a driving simulator, questionnaires, eye tracking glasses, and a wearable collecting biometric data). Besides the design of the experiment, a practical contribution is the actual collection of this comprehensive dataset for 60 participants, including driving and eye tracking data that are equivalent to 60 hours of driving (roughly).

Results of this study practically give insights on the impact of interventions on safety–critical events, including VRU interactions and tailgating, but also of distraction on the above safety–critical events. Moreover, the impact of distraction on those events has been assessed, by means of (but not limited to) eye tracking glasses; this allowed us to highlight the usefulness of visual tracking for monitoring and behavioral analyses. Further, human factor impacts have been assessed, including the influence of socio–demographics on driving behavior, but also the impact of perceptions and attitudes towards driving. Notably, the use of technology acceptance model for representing drivers' acceptance of ADAS in the context of driving simulators has been validated, but also extended to other modes (beyond cars). The latter has highlighted the possibility of transferability of findings across modes: in this case from car to truck (and partially to tram) driving simulator(s), which can pave the way to understanding the extent to which findings can also be transferred from simulator to real–road conditions.

1.5. Thesis outline

The dissertation is structured as follows.

Chapter 2: Driving Behavior Data Handling. This chapter provides a detailed review on data handling for driving behavior, structured between Section 2.1 (a comprehensive review leading to the development of a data–knowledge–information cycle) and Section 2.2 (a review of data handling practices followed in previous projects, allowing the extraction of lessons learned and the development of adequate data handling protocols for NDS).

Chapter 3: Methodology. This chapter presents the overall dissertation methods, including best practices for experimental design (Section 3.1), analysis methods (Section 3.2), and technology acceptance assessment (Section 3.3).

Chapter 4: Experimental Set–up. This chapter presents the experimental set–up (the i–DREAMS case study), based on which the methodology will be applied, and which is the basis for the experimental design, data collection, and analysis. In particular, this chapter will first present the context for the experiments in Section 4.1, after which the developed data handling within the context of this case study will be detailed (Section 4.2), followed by the driving simulator experimental design (Section 4.3) and the naturalistic driving experimental aspects (Section 4.4); the different experimental approaches are based on the guidelines detailed in Chapter 3.

Chapter 5: Data Collection and Analysis. This chapter presents the data collection and analysis efforts made for this dissertation, including the practical aspects of the experimental design for the data collected in Germany (Section 5.1), followed by a summary of the data collected (Section 5.2), processed (Section 5.3), and analyzed (Section 5.4).

Chapter 6: Modeling Results. This chapter presents the model results based on the data collected and analyzed in Chapter 5, taking into account the insights revealed by the initial data analysis. In particular, a special focus is given on modeling drivers' perceptions and acceptance of the experienced system (Section 6.1), after which the different datasets resulting from the data collected in this work are integrated; for the latter, the integrated datasets are used to develop panel regression models to better capture the individual differences between participants (Section 6.2).

Chapter 7: Discussion and Conclusion. This chapter first discusses (in Section 7.1) the main results obtained in Chapter 6, focusing on findings from the technology acceptance model, the developed panel regression models, and the potential transferability of findings across modes. Then, this chapter highlights the contributions of this dissertation (Section 7.2), summarizing the main findings from the different chapters. Finally, the chapter presents the limitations, but also highlights the opportunities for future work, building on findings from this dissertation (Section 7.3).

2. Driving Behavior Data Handling

This chapter presents the results of an extensive literature review on driving behavior data handling and is structured in two parts as follows: Section 2.1, a review leading to the development of a data–knowledge information cycle for driving behavior modeling, and presented in Al Haddad and Antoniou (2022), and Section 2.2, focusing on data handling in naturalistic driving studies, presented in Al Haddad, Alam, et al. (n.d.).

2.1. Data–knowledge information cycle

Naturalistic driving studies and field operational trials are used to collect meaningful data on drivers' interactions in real–world conditions. On the other hand, information extraction methods allow to predict or mimic driving behavior, by using a set of statistical learning methods. In simple words, the way to understand drivers' needs and wants can be represented in a data–information cycle, starting from data collection, and ending with information extraction. The section below will present findings that were presented in Al Haddad and Antoniou (2022), focusing on the data collection part. In this paper, a thorough review was conducted with following keywords: "data collection", "information extraction", "AVs", while keeping the focus on driving behavior. The resulting review led to a screening of about 161 papers, out of which about 30 were selected for a detailed analysis. In this dissertation, we will focus on part of the findings presented in Al Haddad and Antoniou (2022), pertaining to data collection, but also on the insights obtained from that study, as the part regarding automation and autonomous vehicles (presented in the above–mentioned paper) is not relevant for this dissertation.

The analysis included an investigation of the methods and equipment used for data collection, the features collected, and the size and frequency of the data, along with the main problems associated with the different sensory equipment[1]. This paved the way to the development of a framework for data analytics and fusion, which allows the use of highly heterogeneous data to reach the defined objectives; in this dissertation for instance, modeling driving behavior and understanding the acceptance of advanced warning–monitoring systems across various modes, or the transferability of such findings across modes[2].

[1]Compared to the published study, we will omit the detailed analysis on the information extraction coming from studies on "autonomous vehicles", as they are irrelevant for this dissertation.

[2]Compared to the original published study, we will only discuss road–related studies, and will not focus on other transport sectors such as maritime, and air transport, as they are irrelevant for this dissertation.

2.1.1. Background, objectives, and contributions

With improved technology and advances in big data analytics, it is now possible to obtain data from different sensors and sources, and merge it in such a way that it is useful for analysis. This is usually the case of naturalistic driving studies, where driving data is collected by means of a set of sensors, often resulting in thousands of driving hours and millions of kilometers of continuous driving (Knoefel et al., 2018a; Antin et al., 2019). This of course leads to many challenges, such as data heterogeneity, quality (Yadawadkar et al., 2018; Wijnands et al., 2019), and abundance (Simons-Morton et al., 2015; Blanco et al., 2016; Antin et al., 2019; Lex Fridman et al., 2019), etc. In an attempt to understand the process of driving behavior modeling and technology acceptance, one should consider the different steps starting from the proper data collection, and ending with the analytics and fusion of heterogeneous data, which would then allow the extraction of the required knowledge. An analysis of the literature shows that there is a gap in representing these different steps as part of a data–information–knowledge cycle, which would encompass the various aspects starting from data and ending with the knowledge.

The main objective here, and as elaborated in Al Haddad and Antoniou (2022), is to better represent this data–knowledge cycle, through a thorough literature review, which aims to give insights into its different components, including the analytics and fusion frameworks, which could be transferable to different modes and research objectives. To the best of our knowledge, this has not been done before, as previous studies focused on specific aspects of data collection or information extraction, separately.

When planning for a new research project, in which data has not already been collected, or in which data is not derived from a previous project, there is a need to start from the first step of acquiring data through an inevitable data collection scheme, followed by many key components such as processing data or storing it, after which knowledge can be generated. Previous research in this area has focused on either data collection, or knowledge extraction, separately, but rarely, if ever, both aspects were mentioned and discussed together. Having this overview would be crucial as it could help better planning for this cycle in which data is first collected, and then useful knowledge for modeling driving behavior could be generated. This is important from a policy point of view since it would allow to have this entire overview and help to better plan new projects, by considering the different challenges that pertain to different components of this cycle. New type of generated knowledge could for instance be the different driving styles, or driving maneuvers, resulting from in-vehicle data collection, or even user acceptance on ADAS, based on questionnaires or interviews, etc. Different challenges identified from previous research could pave the way to a better planning for future research. Data collection for instance is often associated with challenges pertaining to data processing, data quality, data privacy, or other external considerations. Putting these challenges in one framework would help drafting a checklist that can be used before planning for future research on driving behavior modeling.

The contribution of this review would then consist of this holistic framework of analytics and fusion, which can be extended depending on the research question. In essence, the objectives and findings of this work could be structured along following research questions:

1. How is driving behavior data collected?
2. How is knowledge extracted to model driving behavior?
3. How can a data–knowledge cycle be represented to include various aspects of analytics and fusion for driving behavior modeling?

2.1.2. Methodology

In this section, the methodology followed in this particular study is presented in detail. To answer the research questions defined in Section 2.1, an extensive review has been conducted, which will be reported following some common key items from the PRISMA guidelines (Moher et al., 2010), such as the eligibility criteria, information sources, search strategy, etc., study selection. A collection of relevant literature was done by searching in Scopus, Google Scholar and IEEE Xplore, with an aim to collect studies focusing on in–vehicle data collection and information extraction. Therefore, to answer the defined research questions, following keywords were used in the different search engines: "data collection", "information extraction" (to get insights on data collection), "autonomous vehicles", but also "autonomous driving" (to get insights on driving behavior for highly automated vehicles). Particularly, different combinations of these keywords were entered in the search engines, namely "autonomous vehicles" AND "data collection", "autonomous vehicles" AND "information extraction"; the search was also done using "autonomous driving" in place of "autonomous vehicles"[3]. As mentioned in Section 2.1.1, partial results presented in this paper will be elaborated in this dissertation, mostly for driving behavioral modeling, but not the ones focusing on AVs.

The search was completed by September 2020, and included literature in English, focusing on transportation topics. Additionally, about five references in the literature were included, following "backwards snowballing". A total of 161 studies were eventually collected, covering road transportation, which were first classified by mode (passenger cars, buses, trucks, bikes, or not specified, usually referring to studies collecting and describing highway environments without being specific to a mode.), and level of automation[4] (conventional vehicles, and automated vehicles such as semi–autonomous, fully–autonomous). Upon initial screening, various topics were identified, based on which a classification was made, according to the following categories: "data collection", "driving behavior", "Naturalistic Driving Studies (NDS)", "statistical analysis", and "big data".

Initial screening was made by reading the abstract first, then scanning the contents, and finally going more in depth into the paper when otherwise unclear. Mode classification was important to see the most dominant modes across these studies. The other categories were useful to highlight the fields of contribution made by each paper. "Data collection" referred to studies where procedures of the experiments were described, along with the

[3] While "autonomous vehicles" as a term could refer to highly automated vehicles, it might be the case that some studies were missed for not using the term "automated vehicles", which can be a limitation of the keywords search.

[4] As mentioned before, this is not of interest for this dissertation, but will still be kept in the table, to remain faithful to the published journal paper Al Haddad and Antoniou (2022).

devices and sensors used, size of data, and aspects of data handling. “Driving behavior" referred to all studies whose aim were to classify different driving styles or traits that helped better understand driving characteristics. “Naturalistic driving studies" were ones where the main data was part of an NDS, as described by the authors themselves. Further, "statistical analysis" referred to studies where statistical models were elaborated to extract information and features, useful generally to model driving behavior. Finally, “big data" referred to studies focusing on big data tools and methods for modeling, processing, analyzing and visualizing transport and mobility.

From an initial screening of abstracts, it was obvious that most papers could either answer the first research question (on the collection of driving behavior data), or the second (on knowledge extraction for modeling driving behavior). Furthermore, we did not find any contribution which holistically elaborated on the different steps going from data collection (and challenges faced) to information extraction (based on that same collected dataset). We therefore split the initially collected papers in two subsections, one for data collection (mostly found in papers addressing conventional vehicles), and the other for information extraction (in which we focused on findings in papers tackling AVs). The aim was to eventually combine findings from each of these sub–sections in order to answer the third research question, which would then be a bridge between both, and a transition to future research on AV behavioral modeling.

A full list of the primarily selected papers is partially presented in Table 2.1. Finally, these papers were screened, and a subset of 27 studies were selected[5], to be analyzed in further detail. These were studies that fit best the scope of the research objective: modeling driving behavior by looking at data collection aspects, and information extraction. This means the primary focus was given on driving behavior as a common interest factor. For example, some studies were removed as they were not concerned with driving behavior; this includes studies on image classification and vehicle detection (Ghandour, Krayem, and Gizzini, 2019), work zone sign detection (Seo, Wettergreen, and W. Zhang, 2012), traffic sign estimation (Vu et al., 2013), text recognition (Balaji, Kumar, and Sujatha, 2017), road investigation under weather conditions (Cheng, Z. Wang, and Zheng, 2017), driver and vehicle recognition (Mo, Gao, and Q. Zhao, 2017). Moreover, studies which presented the same or similar outcomes from the same authors, describing the same projects, were removed from the final selection. The selected papers were finally presented in Table 2.2, and elaborated in Section 2.1.3. The presented methodology is summarized in Figure 2.1; in this figure, the dashed rectangle represents the focus of this dissertation, as compared to the initial figure and methodology that was part of Al Haddad and Antoniou (2022).

[5] Table 2.1 only presents 20 out of these studies, which were studies for conventional vehicles, as AV studies were out of the scope of this dissertation.

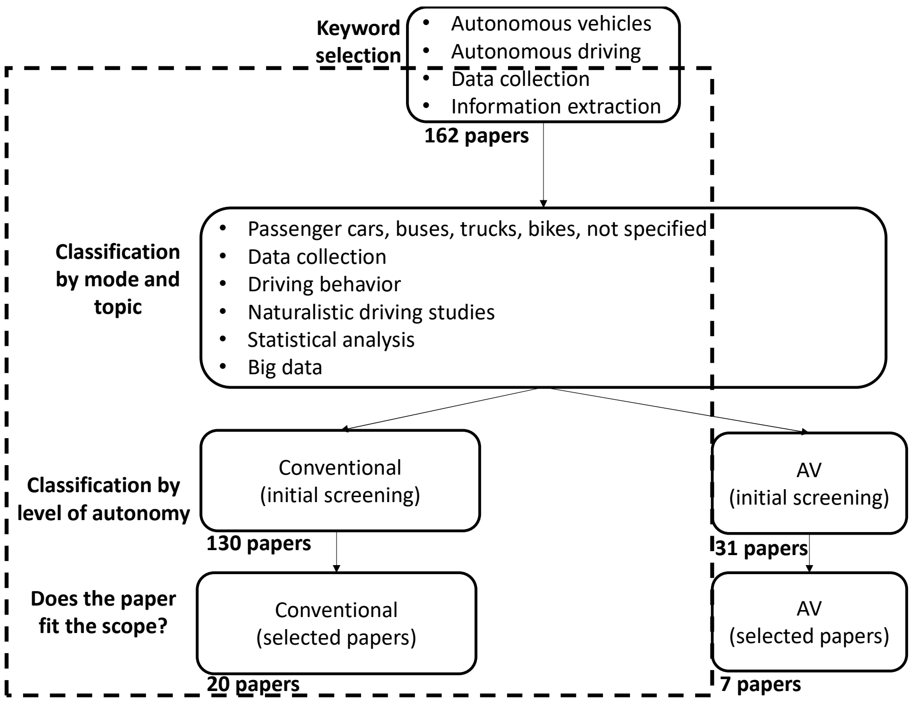

Figure 2.1.: Methodology for paper selection *(own illustration, adapted from Al Haddad and Antoniou (2022); the dashed rectangle represents the papers discussed in this dissertation.)*

Table 2.1.: Initial set of screened papers (conventional vehicles); *source: Al Haddad and Antoniou (2022)*

Study	**Cars**	**Buses**	**Bikes**	**Not specified**	**Data collection**	**Driving behavior**	**NDS**	**Statistical analysis**	**Big data**
Jacob and Rabha (2018)	•				•				
Yan et al. (2019)	•					•			
Morgenstern, Schott, and Krems (2020) and Patil, Adornato, and Filipi (2009)	•						•		
Bosi et al. (2019)	•								•
Ehsani et al. (2020), Itkonen, Lehtone, and Selpi (2020), Koppel et al. (2020), Kovaceva, Isaksson-Hellman, and Murgovski (2020), R. Li et al. (2020), Petzoldt (2020), Yasmin, Hu, and Luo (2020), Ding et al. (2019), Muronga and Ruxwana (2017), Thomas A. Dingus et al. (2016b), T. Dingus et al. (2006), Simmons, Hicks, and Cair (2016), Bruce Wallace, Puli, et al. (2016), Tivesten and Dozza (2015), Fitch et al. (2014), Montgomery, Kusano, and Gabler (2014), Tian et al. (2014), Tivesten and Dozz (2014), Wege, Wil, and Victor (2013), Myers, Trang, and Crizzle (2011), Adornato et al. (2009), Sheila G. Klauer, Thomas A. Dingus, et al. (2006), and Sayer, Devonshire, and Flannagan (2005)	•					•	•		
Y. Wang and Ho (2018)	•					•		•	
K.-F. Wu and P. P. Jovanis (2013), K.-F. Wu and P. P. Jovanis (2012), Y. Liang, J. D. Lee, and Yekhshatyan (2012), and P. P. Jovanis et al. (2011)	•						•	•	
Samiee et al. (2014)	•							•	•
Antin et al. (2019), Barnard et al. (2016), Blatt et al. (2015), Simons-Morton et al. (2015), Sheila G. Klauer, F. Guo, et al. (2014), Ott et al. (2012), and Neale et al. (2005)	•				•	•	•		
Ma et al. (2021), Xia et al. (2018), and Warren, Lipkowitz, and Sokolov (2019)	•				•	•		•	
Das, Khan, and Ahmed (2020), X. Liang (2020), S. Li et al. (2020), Rasch et al. (2020), Alekseenko et al. (2019), Arvin, Kamrani, and Khattak (2019), Hochin, Shinohara, and Nishizaki (2019), Kuo et al. (2019), G. Li et al. (2019), Thapa et al. (2019), G. Wang, P. Sun, and Y. Zhang (2019), Yadawadkar et al. (2018), Precht, Keinath, and Krems (2017), Carney et al. (2015), F. Guo, Fang, and Antin (2015), Hallmark et al. (2015), Victor, Dozza, et al. (2015), Foss (2014), Jonasson and Rootzén (2014), Bagdadi (2013), F. Guo and Fang (2013), Valero-Mora et al. (2013), Ahlstrom et al. (2012), J. D. Davis et al. (2012), F. Guo, Sheila G. Klauer, et al. (2010), Shankar et al. (2008), and Q. Lin et al. (2008)	•					•	•	•	
Dawson (2019) and Bruce Wallace, Knoefel, et al. (2017)	•					•	•		•
Chun et al. (2019)	•					•		•	•
Barbier et al. (2019), Chhabra, Verma, and Rama Krishna (2019), and Yadawadkar et al. (2018)	•				•	•	•	•	
Rosales et al. (2017)	•					•	•	•	•
Lex Fridman et al. (2019)	•				•	•	•	•	•
Blanco et al. (2016)		•			•	•	•		
Barnard et al. (2016), Soccolich et al. (2013), and Hickman and Hanowski (2012)		•				•	•		
Aihara, Bin, and Imura (2019) and Barr et al. (2011)		•				•	•	•	
Dozza, Piccinini, and Werneke (2016), Dozza and Werneke (2014), and Espié et al. (2013)			•		•	•	•		
Kovaceva, Nero, et al. (2019)			•			•	•	•	
Bachechi and Po (2019), Fan et al. (2019), S. Kaur, Singh, and D. Kaur (2019), Piedad et al. (2019), Pop and Prostean (2019), S. Zhao et al. (2019), Abodo et al. (2018), Bellini et al. (2018), Kaushik, Wood, and Gonder (2018), Mo, Gao, and Q. Zhao (2017), Al-Najada and Mahgoub (2017), and McLaughlin, J. M. Hankey, and Thomas A. Dingus (2008)				•				•	
Fernandez-Rojas et al. (2019), Xiaodan Liu and C. Li (2019), Moharm et al. (2019), Pucci and Vecchio (2019), Zhu et al. (2019), Figueiras et al. (2018), Gohar, Muzammal, and A. U. Rahman (2018), M. Park, Koo, and Kim (2018), Torre-Bastida et al. (2018), and Schatzinger and Lim (2017)				•					•
Kaushik, Wood, and Gonder (2018)				•	•			•	
Mishra et al. (2020), Sangster, Rakha, and Du (2013), and S. E. Lee, Olsen, and Wierwille (2004)				•		•	•		
J. Guo et al. (2018) and Chunqing Zhao et al. (2017)				•		•		•	
F. Guo (2019) and McLaughlin, J. M. Hankey, and Thomas A. Dingus (2008)				•			•	•	
Guan et al. (2019), Guleng et al. (2019), Kang, Kwon, and S. H. Park (2019), Nallaperuma et al. (2019), Serok et al. (2019), Sivasankaran and Balasubramanian (2019), and J. Zhang et al. (2019)				•				•	•
Knoefel et al. (2018a)				•	•	•	•		
C. Sun et al. (2018) and Vu et al. (2013)				•	•			•	•
Zhou et al. (2019)				•		•		•	•

2.1.3. Literature findings

Data collection

In this section, the main review findings on data collection are presented, with an aim to answer the first research question on how driving behavior data is collected. These are based on the selected studies from the initial set of screened papers, where in–vehicle data was collected. Particularly, highlights are provided for used methods and equipment, features collected, and size and frequency of data. Studies selected for analysis are presented in details in Table 2.2 and are the ones mostly focusing on data collection processes aiming at driving behavior investigation[6].

Methods and equipment

As previously mentioned, studies focusing on in–vehicle data collection, for the purpose of driving behavior analysis, are mostly field test trials, or naturalistic driving studies. The latter are studies where data is collected unobtrusively, by instrumenting drivers' vehicles and monitoring their behavior, including the collection of "baseline data", reflecting their "normal driving" (Carsten, Kircher, and S. Jamson, 2013). The aim is to investigate associations between different variables, but also to extract risk factors in safety–critical events, and classify drivers according to different profiles. Such studies cover usually road transportation modes, particularly passenger car vehicles. In a simplified manner, the collected data covers different components, which are presented here under: **vehicle data**, **environment and context data**, and **driver data**.

Vehicle data is collected through vehicle instrumentation, including video camera[7], and sensor technology, often integrated in a Data Acquisition System (DAS) in cars (Antin et al., 2019; Knoefel et al., 2018a; F. Guo, Fang, and Antin, 2015; Simons-Morton et al., 2015; Carney et al., 2015; Valero-Mora et al., 2013; Myers, Trang, and Crizzle, 2011; Lex Fridman et al., 2019), trucks (Blanco et al., 2016; Hickman and Hanowski, 2012), and bikes (Dozza, Piccinini, and Werneke, 2016; Espié et al., 2013). DAS often includes several units, cameras, and sensors like accelerometers, gyroscope and rate sensors, GPS, radar and radar interface box (Antin et al., 2019), and an OBD connector to measure on-board-diagnostics of the vehicle; sometimes audio data is recorded as well (Blanco et al., 2016).

External, context, or environment—related data is supplemental, out–of–vehicle data, which could include roadway (Victor, Dozza, et al., 2015) and weather information (Carney et al., 2015; Knoefel et al., 2018a). While weather data can be measured in–vehicle by meteorological sensors, it can also be referred to as context or external data if obtained from

[6] In this table, highlights of the papers are presented, including useful findings (+), but also challenges or limitations (-). These highlights are of course based on a subjective classification by the authors of this paper, and some challenges (e.g., the huge datasets collected) could be as well considered as great assets and strengths of the same studies. Finally, distances reported to miles have been converted to kilometers (kms) to keep one unit system in the table, for comparison and consistency purposes.

[7] Although video data can record data from the road ahead or the drivers' faces, etc., this would still be classified as vehicle data, since the data source is the vehicle itself, as the camera is installed in the vehicle.

other sources, and later merged to the existing data. This is also the case for instance for accidents datasets, which can be added a posteriori if obtained from police reports.

Finally, **driver data** pertains to drivers' demographics and health conditions, and includes questionnaires, assessments, or diaries, as often done in bike and truck experiments (Dozza, Piccinini, and Werneke, 2016), or even post—experiment interviews (Espié et al., 2013). Additionally, driver data can be collected from mobile phone records, where participants' mobile phones could be paired with the vehicles (Lex Fridman et al., 2019).

Features collected

Distinct data types are collected from the methods and equipment used, allowing the collection of different features. Data collected can be classified under vehicle data, environmental or context data, and driver—related data. Vehicle data is mostly **dynamic data** (in–vehicle sensor data and video and images data); these are time–series data including kinematics variables or driving parameters such as: acceleration, speed, position on the road, distance to other cars, type of road, radar and GPS and computer data (Knoefel et al., 2018a), yaw rate, network data (F. Guo, Fang, and Antin, 2015), steering wheel rotation angle, brake pressure [as in the PROLOGUE project (Valero-Mora et al., 2013)]. Video and image data can be collected from multiple cameras (forward, and rear windshields) providing images of the drivers' face, or the cabin conditions as in Antin et al., 2019. In addition to video data, audio data is sometimes recorded (Carney et al., 2015). This data category can be considered dynamic, since it is recorded continuously and collected in real time. Supplemental data includes environmental and context data like maps, weather, or other data like roadway (workzone), data, or crash investigation or reports. Mobile phone records can also be used as an additional data source (Antin et al., 2019). Such data types (weather, roadway databases, etc.), cannot be considered real–time or continuous in the same manner as in—vehicle data, and therefore will be referred to as **static data** in this research. In particular, while map and weather data can be derived using GPS coordinates and can be registered and updated real–time, they are considered static in this representation, as usually, and based on previous research, their corresponding time–series are not usually used real–time for classifying driving behavior. As mentioned previously, both can be categorized as context data as they are used to enrich the existing datasets. For instance, weather data can be used as an indication of the task complexity, and it might be more interesting to know the weather condition, e.g. rainy or sunny, simply for a longer period of time, for instance a trip duration.

Finally, driver data includes characteristics from surveys, but also assessment or medical examinations. This data type will also be considered static, since it also does not change in a continuous real—time manner. For instance, Simons-Morton et al. (2015) administered a stress inducing test to test drivers' stress responsivity; while these test results can theoretically change, these tests and therefore their corresponding data are often collected only once (or more times) during the experiments and are therefore cross–sectional. Additionally, biometric data of the driver, such as heart rate data or other physiological measurements, can be continuously collected (using for instance wearables); this would then be considered as dynamic and objective data. The presented data (vehicle, environment, and driver) can be further classified into **objective data** (which does not depend on the drivers' own judgments and perceptions, but is rather collected through sensors, or other objective assessments), or **subjective data** [including self–reported information including participants' diaries, own points of views on safety–critical events through interviews or questionnaires, or even expert assessment of skills, and video coding of events (Hickman and Hanowski, 2012). Based on the collected data, features can be extracted covering mostly crash and near–crash data (Antin et al., 2019), and crash risk assessment (Knoefel et al., 2018a). Safety–critical events are often calculated upon exceeding specific thresholds. For instance abnormal driving is triggered by high acceleration or other kinematic factors: F. Guo and Fang (2013) recorded 8 seconds before and 4 seconds after the trigger. In other words, going from the raw collected data, derived data is often calculated, by using statistical methods to evaluate risk or measurements of interest. For instance, statistical modeling of collected data can help reducing the data (e.g. PCA), or assess risk and driver profiles (F. Guo and Fang, 2013).

Other road transport modes collect similar features through comparable data collection equipment; for example in a truck study, both audio and video data were used, in addition to actigraphy devices to monitor sleep quantity, since fatigue is often a parameter of interest for professional drivers and long driving hours (Blanco et al., 2016). For Powered-two wheelers, participants' points of view are often of interest. Subjective data is therefore collected by interviewing participants after the experiments to better understand critical events (Espié et al., 2013; Dozza, Piccinini, and Werneke, 2016). Also, other modes often collect additional data that drivers themselves flag in safety-—critical situations, by pushing an incident button (Blanco et al., 2016; Dozza, Piccinini, and Werneke, 2016). Overall, we can present data on two axes, to summarize its type and source: the x–axis describes the frequency with which data is collected (static and/or dynamic), and the y–axis presents whether data is rather "unbiased" or more subject to personal judgments and perceptions (subjective and/or objective). This classification, stemming from analyzing previous research, can be useful for representing the different dimensions of the data and is visualized in Figure 2.2 below.

Size and frequency of data

Field operational tests and NDS often result in up to millions of kilometers of driving data, covering millions of trips, for an equivalent of hundreds of thousands of hours, which often translates into several thousands of crash or near—crash events[8]. As part of the Second Strategic Highway Research Program (SHRP 2), over 50 million kilometers of continuous data was collected from over 3500 drivers across the Unites States, an equivalent of over 900,000 hours of in-vehicle time, and 5.5 million trips. The study captured more than 1900 light-vehicle crashes and 6900 near-crashes, an equivalent of five petabytes of data (Antin et al., 2019). In the Candrive study (Knoefel et al., 2018a), data was collected data from 256 drivers in Ottawa, Canada, monitored for up to five years each, amounting to a total of more than 15 million kilometers driven, the equivalent of one terabyte of storage data. The

[8]In this section, the size and frequency of data collected often reflect the data collection effort made within the NDS based on which the studies/papers were written; in other words, they are not data collected individually by the authors of the papers presented but belong to larger–scale studies.

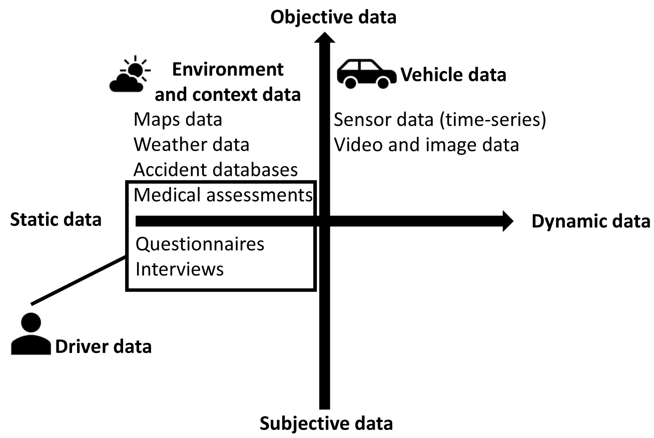

Figure 2.2.: Collected data by source and type (*source: Al Haddad and Antoniou (2022)*)

naturalistic teenage driving study itself collected 18 months of driving data (Simons-Morton et al., 2015). In the 100–car Naturalistic Driving study (F. Guo and Fang, 2013), data was collected throughout one year, resulting in three million vehicle kilometers, the equivalent of 43,000 hours of data. Another study (Q. Lin et al., 2008) collected data from 50 taxis in urban areas for 10 months using video drive recorders in Beijing, China, collecting a total number of 2440 of valid events, including 40 accidents. Studies featuring other road vehicles also collected huge amounts of data. Dozza, Piccinini, and Werneke (2016) collected 1500 kilometers of biking data, including 88 critical events in Sweden in all environments. Hickman and Hanowski (2012) collected data from 183 commercial truck and bus fleets comprising 13,306 vehicles and included 1085 crashes, 8375 near–crashes, 30,661 crash-relevant conflicts, and 211,171 baseline events. Blanco et al. (2016) collected more than 14,500 driving hours of valid truck data from approximately 2,200 driving shifts and 26,000 on-duty hours of daily activity register data, from more than one million kilometers of driving, an equivalent of eight terabytes of data storage. Overall, what these numbers can tell us is that collected in–vehicle data often results in several thousands of hours of driving data, millions of kilometers of data, and non-negligible storage needs.

However, for the above studies, the ratio of storage (in terabytes) to driving data collected (in hours) is not constant. This variation is due to the varying sensor frequencies, but also whether or not video data has been collected. This variation in frequency is a challenge for data collection and processing; sensors and cameras often collect data and images at different frequency. For instance, Dozza, Piccinini, and Werneke (2016) collected data continuously at 100 Hz for all signals, video data at 30 Hz, and GPS data at 10 Hz. Valero-Mora et al. (2013) (PROLOGUE) also collected vehicle data at 100 Hz, video data at 25 Hz, and eye tracking data at 60 Hz. In this study, while vehicle data was automatically synchronized, eye tracking needed to be manually synchronized with vehicle and video data. In the 2BeSafe project (Espié et al., 2013), vehicle dynamics were collected at 1000 Hz, while video data was collected at 12.5 Hz and GPS data at 1 Hz. In SHRP 2 (Antin et al., 2019), video data was collected at a frequency of 15 Hz and sensor data at 10 Hz. In Candrive (Knoefel et al., 2018a), GPS and computer data were collected at a frequency above 1 Hz. In Blanco et al. (2016), accelerometer data was collected at a 10 Hz frequency. This only highlights the need for data synchronization for subsequent data analysis; for a perfect synchronization of multiple data streams in post–processing, data has to be timestamped (Lex Fridman et al., 2019).

The main highlights of these studies, as noted in the "Remarks" column of Table 2.2 are: i) data collection often results in a huge volume of data, which is challenging to manage, in terms of both time and costs, ii) data quality is of utmost importance, e.g., missing data can be a challenge in asynchronous data, iii) statistical techniques (data reduction, clustering, annotation and fusion of spatial and temporal info) can avoid computationally expensive pre–processing steps, iv) phone sensors can complement traditional data collection techniques, v) additional driver data (diaries, interviews, and flagged events) can help complement collected vehicle data and boosts interpretability.

Table 2.2.: Selected papers focusing on data collection aspects (*source: Al Haddad and Antoniou (2022)*)

	Mode	Data collection equipment					Features collected				Size/Frequency	Remarks
		Sensors	Cameras	GPS	Radar	OBD	Video/Image	Vehicle Kinematics	Subjective data	Other		
Ma et al. (2021)	Cars, buses, trucks	•							•	•		(+) Objective and subjective factors were considered to analyze factors contributing to perceptual bias of aggressive driving (+) Objective factors include penalty points, subjective factors include self–assessment of aggressive driving
Antin et al., 2019	Cars, SUVs, pickups, trucks	•	•	•	•	•	•	•	•	•	* Videos: 15 Hz * Cabin images: 1/10 min * Time-series: asynchronously * 51 million kms of driving data: 5 PB of data	(-) Large and complex database
Lex Fridman et al., 2019	Cars	•	•	•		•	•	•	•	•	*511 000 kms of driving data: 100 000 GB *7.1 billion video frames *CAN sensors: 1GHz processor *Cameras 30 Hz *Data has to be timestamped to allow perfect synchronization of multiple data streams in post-processing	(+) Computer vision–based analysis of human behavior (+)ADAS functions including ACC, pilot assist, blind spot monitor (+) Semi–automated annotation (-) Huge data
Warren, Lipkowitz, and Sokolov, 2019	Cars	•	•	•			•	•		•		(+) Phone sensors can complement traditional data collection techniques (+) Less costly and time consuming (+) In-phone sensors (+) Clustered drivers based on driving behavior: flag what deviates from the norm
Wijnands et al., 2019	Cars	•	•				•	•		•	* 30 frames per second	(+) Detection approach on a mobile phone (+) Early fusion of spatial and temporal information (+) Balance between high prediction accuracy and real time inference requirements (+) Avoids computationally expensive pre-processing steps
Knoefel et al., 2018a	Cars	•	•	•		•	•	•		•	*15 million kms: 1 TB data storage * GPS and computer data:>1Hz	
Yadawadkar et al., 2018	Cars	•	•		•	•	•	•	•			(+) Identifies driver distraction and drowsiness (+) Insights into data from collection from DAS to feature extraction (+)No video data (-) Data reductionists reviewed coded and evaluated events (-) Timing of data across variables asynchronous, leading to missing variables at each collection time point (-) Missing value replaced by last corresponding known value
Blanco et al., 2016	Trucks	•	•	•	•		•	•	•	•	*1.2 million kms: 8 TB data storage	(+) Additional data from driver incident button, activity registers, extended medical assessments, and actigraphy or sleep devices (-) Data volume
Dozza, Piccinini, and Werneke, 2016	E-bikes	•	•	•	•		•	•	•	•	*Sensor data: 100 Hz *Video data: 30 Hz, GPS data: 10 Hz	(+) Push-buttons for critical events, trip diaries, and post-experiment interviews help complementing objective data
Carney et al., 2015	Cars						•	•	•	•	*Videos: 4 Hz	
F. Guo, Fang, and Antin, 2015	Cars	•	•	•			•	•				
Simons-Morton et al., 2015	Cars	•	•	•			•	•	•	•		(-) Data volume
Espié et al., 2013	Powered two-wheelers	•	•	•		•	•	•	•		*Vehicle dynamics: 1kHz frame rate, with 4µs time data stamping Video data: at 12.5 Hz GPS at 1 Hz	(+) Combine subjective data with objective data (-) Cost
F. Guo and Fang, 2013	Cars	•	•	•	•		•	•	•			
Valero-Mora et al., 2013	Cars	•	•	•	•		•				* Vehicle data: 100 Hz; synchronized automatically with the video data (25 Hz) * Eye tracking data: 60 Hz; needs manual synchronization with vehicle and video data	(+) Highly instrumented vehicles can complement studies using a large number of standardized vehicles (-) Large amounts of data can be challenging to manage
Hickman and Hanowski, 2012	Trucks and buses	•	•	•			•	•				(+) On-board monitoring systems to identify safety-critical events
Ott et al., 2012	Cars		•				•			•		(-) Uncontrollable environmental factors may affect the validity of the road test
Myers, Trang, and Crizzle, 2011	Cars			•		•	•	•	•	•		
Q. Lin et al., 2008	Taxis	•	•	•	•		•	•	•			(+) Investigation of causes of rear-end conflicts (-) Data volume
Neale et al., 2005	Cars	•	•	•	•	•	•	•		•	* 3.2 million kms * 43 000 hours of data	(+) Hard drive large enough to store data for several weeks (+) Independent sensing systems (+) Detection systems for headway, side obstacle (+) Incident box for drivers to flag incidents

2.1.4. Proposed data–information–knowledge framework

Data analytics framework

By looking at different components from the moment data is collected, until it becomes useful for behavioral modeling, and further assessments, a data analytics framework can be drawn, and is visualized in Figure 2.3[9].

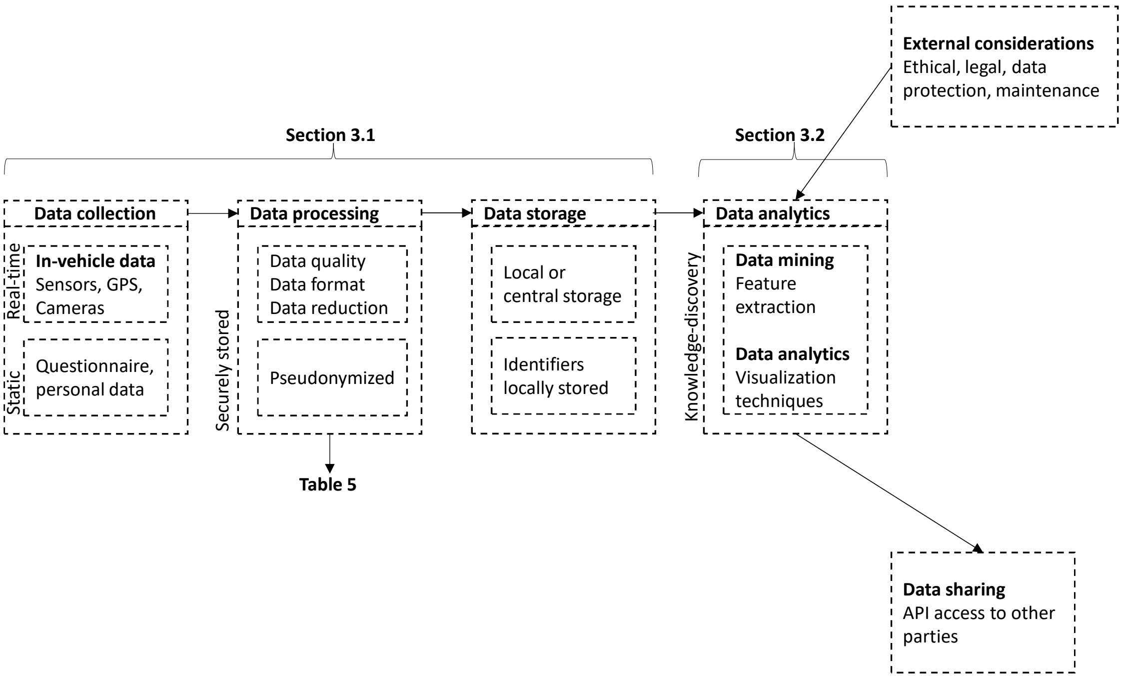

Figure 2.3.: Proposed data analytics framework (*source: Al Haddad and Antoniou (2022)*)

In this framework, the data collection component includes data captured in (in this dissertation) in-vehicle experiments, where in-vehicle sensors collect data continuously/real–time to monitor driving behavior. This can include GPS, cameras, sensors, which often do not collect data at the same frequency. This would then inevitably include pre–processing of the data to ensure first that there are no proper communication issues and that signals measure data correctly, make it available and process it, but also that different sensors are fused where possible, to ensure timestamped synchronization. In experiments, data often includes subjective data as well as questionnaires from participants or drivers, which would then have to be properly linked to the field data; these however are not dynamic in general, or at least less dynamic, and so they would need to be managed differently.

Data processing includes aspects of data quality, which can be checked through different

[9]Please note that Figure 2.3 is the original presented in Al Haddad and Antoniou (2022), and therefore, sections that are mentioned refer to the ones from the original manuscript.

methods, ranging from filtering, noise cleaning, to manually controlling for consistency in the collection; for example for eye tracking measurements, synchronization is done with vehicle and video data.

Data mining can include methods like classification and clustering, feature extraction using machine learning methods, pattern recognition, predictive analysis, and visualization techniques with dashboard-based elements. The idea would then be that once data is made available, data could be processed in such a way to predict the needs of the drivers accurately and safely.

The different components presented also need to follow ethical, legal, and privacy standards of the country where the collection is taking place. Looking at previous studies, we can see a pattern in data management where ethical and legal considerations are at the backbone of data collection. Data handling as well, including data storage, and sharing, would need to follow specific standards; in Europe, this means a compliance with the EU Regulation 2016/679, or the General Data Protection Regulation (GDPR), which came in effect from 25 May 2018 (European Commission, 2018), aiming at protecting personal data. Protocols of anonymization or pseudonymization of data at the source should therefore be part of the framework. For instance, for data storage, different techniques exist either involving private or public storage, depending on the usability and purpose. For instance, personal and identifiable data should be locally stored (not publicly), for complying with GDPR. Only pseudonymized data can be associated with the vehicle data and stored in the public storage (pseudonymized or anonymized, depending on regulations). Similarly, for data sharing (and eventually maintenance), different access levels may be defined, according to defined agreements, in order to make different parts of the data accessible to different parties. Specific processing tasks and their descriptions are suggested and elaborated in Table 2.3.

Table 2.3.: Suggested data processing tasks (*source: Al Haddad and Antoniou (2022)*)

Data processing task	Description
Data quality	Labeling or encoding data from test vehicles
	Handling missing data (sensor and communication failure)
	Temporal order for time-series: needed to deal with possible network requests from the collection end to the cloud server that do not arrive in the correct order, or when data is received by the server, but it's acknowledgement does not reach the data collection end
	Handling the timezone information carefully
	Data verification for errors (removing outliers and irrelevant data, cleaning datasets, rectifying GPS data)
	Data loss minimization: to prevent data loss during the data upload/retrieval procedure, it is important to verify that data is consistent before deleting it from the vehicle
	In case of inconsistency, the vehicle data logger should be checked to recognize and fix issues as soon as possible
Data format	According to the desired format
	A description of the data variables should be provided by the technical partners generating the data and should be sufficient for future reference
Data reduction	Reducing data volume mostly for video data. Video data may be pre-processed in a way to reduce data volume without compromising the quality of the video
	Metadata of the videos (event, timestamps, trip info etc.) should also be attached with each video for ease of future analysis
Data pseudonymization	Assigning a unique identifier for each participant to comply with GDPR, and linking the data from participants to vehicle data

Data fusion framework

While the data analytics framework presented above described data fusion processes, these were only at sensor levels, as part of pre—processing or processing steps. A major challenge that has not been addressed is the process of combining heterogeneous data, in a way to obtain meaningful information, and extract an additional layer of information. When thinking of data collected within experiments such as NDS or driving simulator studies, the heterogeneity of data can be translated into elements of driving data, questionnaire data, but also other contextual data (traffic data, accident data). A combination or fusion of information is therefore necessary to develop models that can answer the defined research questions, for instance, ADAS acceptance, and transferability of findings across modes. Data fusion can therefore be achieved at several levels: at a sensor level, or after the first layer of analytics.

Akbar et al. (2018) developed a methodology with two levels of analytics, where events were defined from individual data streams in the first level, to probabilistic complex events after the second level; this can also be referred to as the fusion of these various events, using Bayesian Networks (BNs). In the first level, events of interest are defined and extracted in real time, while in the second level, BNs can take uncertainty while detecting complex events. In particular, the authors of the above–mentioned study (Akbar et al., 2018) used data streams including traffic, weather, and social media data streams from Madrid, Spain. The approach used followed a hybrid framework based on complex event processing (CEP) and Bayesian Networks (BNs) to extract high-level knowledge in the form of probabilistic complex event (in this case the probability of congestion in real-time). The approach was qualitatively (using web-interface) and quantitatively (using F-measure) evaluated, resulting in an accuracy of over 80%. A generalized framework for fusion of different data streams can be adapted from

Akbar et al. (2018). In this framework, different information sources (such as vehicle data, traffic data, or survey data) can be used to modify input parameters of well–known driving behavior models, to then see the impacts (of such changes) on the broader (transport) network level. In the context of modeling driving behavior data, events can be derived depending on data streams and objectives. Data fusion can be of interest as an additional component after the analytics phase (sensor level fusion would already take place in the processing component of the data analytics). Driving behavior data presented in this section mostly included vehicle data, survey data, but could eventually include other data types that would enrich the existing knowledge layer, such as social media data. An inference using an approach similar to the one presented in Akbar et al. (2018) could be help estimating the probability of AV acceptance, using pilot vehicle data, enriched by additional data streams (e.g. social media, to infer general perception towards ADAS for example, and/or questionnaire data).

Transferability across modes

While this study focused on passenger cars for road transportation, the presented frameworks can possibly be extended to other transportation modes/sectors. Though limited, studies researching driving behavior in other transportation modes include similar equipment and collect data that is similar to the one for road transport (as depicted in Figure 2.2). Due to relatively less research in other modes, it becomes interesting to see whether some knowledge can be transferred across modes; several opportunities for such transfer have been highlighted in Papadimitriou et al. (2020). Rail studies for instance also include objective and subjective data, such as GPS data, surveys (Larue and Wullems, 2019; M. Guo et al., 2016), which can help evaluating rail driving behavior at crossings, or even video analytics (Zaman, Xiang Liu, and Z. Zhang, 2018). Such studies also aim to assess risky behavior, or crash or near-crash data, using advanced analytics algorithms.

Considering the knowledge that could possibly be gained by instrumenting vehicles for different transport modes, extracted knowledge from each mode could then be combined to create an overall transferable finding. For instance, in case the research objective is to develop an index for ADAS acceptance, a first level of analytics could be ADAS acceptance per transportation mode; a fusion of multiple indices across different modes could result in an overall ADAS acceptance index. For example, different field experiments or surveys can give insights into the acceptance for given ADAS in a certain region. Generally, most research on this topic is done for road–based transportation, in particular cars; this could be however relevant to other road modes, such as rail, buses, or trucks. While for rail, less interaction between the operator and vehicles is expected, there still might be some relevant insights that could be found on the acceptance of automation for these modes. Such insights on the trust of automation for professional drivers can help transport planners better understand or assess the acceptance for these modes in different cities or regions. Theoretically then, a first level of analytics for ADAS acceptance would help assess acceptance across different transport modes. Taking into account the rich information provided by this first level of analytics, an overall ADAS index could then be drawn from these different indices found, highlighting the factors influencing this acceptance for instance, such as trust, or relevant demographic variables. This is depicted in Figure 2.4, which was also drawn based on the principles described in Akbar et al. (2018). While that might have challenges and obvious limitations (such as the assumptions drawn for such results to hold true; for instance the need of consistent pilot data), the aim of this example was to rather provide an insight on how findings of heterogeneous types could and should be exploited; transport modes can considerably learn from each other mostly in terms of automation and trust (Papadimitriou et al., 2020).

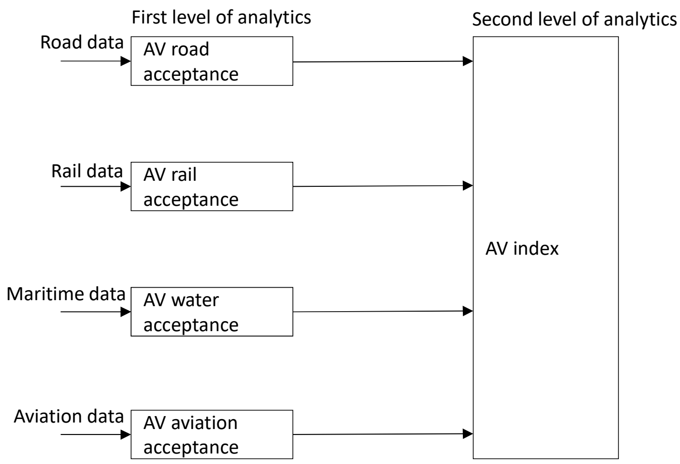

Figure 2.4.: Data fusion framework across different transportation modes (*source: Al Haddad and Antoniou (2022)*)

2.2. Data handling in NDS

As their name indicate, naturalistic driving studies are conducted in a “natural” unobtrusive way in which participants (drivers) drive as they “normally” do, without being asked to drive specific roads, or change their driving patterns. The only difference is that their vehicles are instrumented with data collection devices. With advances of technology and sensory equipment, NDS are increasing in popularity, but also in challenges. Driving for longer periods of time inevitably leads to large amounts of data collected, and therefore creates challenges in terms of data management, data sharing, and data handling in general. While previous projects and studies have indeed followed some guidelines in handling data, there are currently no comprehensive protocols or guidelines for handling data in NDS.

To address this gap, this section aims to contribute to research, and particularly to future NDS projects, by reviewing previous studies and focusing on relevant aspects of data collection, preparation, storage, as well as other ethical and legal considerations. Based on the findings and lessons learned, a methodology for data handling can be developed, which, applied to the relevant case study, can result in the development of suitable data handling protocols; such protocols could be dynamic in that they may be updated along the course of a project, and serve as guidelines or checklists, for quality control, wherein the defined goals and followed guidelines could be cross-checked for validity purposes.

Several components are crucial for handling data in NDS. The FESTA handbook (*FESTA Handbook* 2018) defines the guidelines for data acquisition, including storage and analysis tools, emphasizing the importance of laws and regulations in such protocols. Based on these recommendations, the next subsections present findings and lessons learned from previous projects, focusing on various aspects of data handling, paving the way to the methods proposed in this section.

The reviewed projects are: 100-Car Naturalistic Driving Study (T. A. Dingus et al., 2006), SeMiFOT (Victor, Bärgman, et al., 2021), INTERACTION (FOT-Net WIKI, 2015), 2BeSafe (The University of New South Wales, 2017), OBMS (Federal Motor Carrier Safety Administration, 2021), UDRIVE (2-BE-SAFE, 2012), Canada NDS & Canada Truck NDS (C. Klauer, Pearson, and J. Hankey, 2018), Track & Know (Track & Know, 2021). For some projects, insights were provided by personal communication of researchers who previously worked in one of the projects (for which no or few associated references can be found in the literature).

2.2.1. Data collection

The selected projects cover a wide range of countries, including European countries, the United States, Canada, Australia, and Israel, and multiple transport modes including passenger cars, trucks, motorcycles, or other modes like scooters, buses, or powered-two-wheelers (PTW). Onboard data collection units were installed and used in many studies and included a GPS recorder, accelerometer, camera(s) for road condition and object detection, camera for driver eye and hand tracking (PROLOGUE, 2011; 2-BE-SAFE, 2012; UDRIVE, 2017; 2-BE-SAFE, 2017; Victor, Bärgman, et al., 2021), CAN access (UDRIVE, 2017; Victor, Bärgman, et al., 2021), and other sensors like position control (2-BE-SAFE, 2012; 2-BE-SAFE, 2017; Victor, Bärgman, et al., 2021), alcohol sensors (SHRP 2, 2013), or voice recording sensors activated by incident push buttons (T. A. Dingus et al., 2006; PROLOGUE, 2011; SHRP 2, 2013; The University of New South Wales, 2017; C. Klauer, Pearson, and J. Hankey, 2018).

Based on the data sources, data were categorized into two types: in-vehicle data, and survey data. In-vehicle data are mainly collected from onboard units and include three levels: driver, vehicle, and context data. Driver data contain drivers' manoeuvres: pedal positions, turn signal operation, usage of cruise control, steering wheel rotation angles, and drivers' face image or video. Vehicle data include distance and headway to the vehicle in front, acceleration/deceleration in three axes, speed, and total kilometers (km) driven. Context data comprise natural environment (climate, weather, and noise), artificial environment (line crossings, lane position, road type, locality, and road geometry), and trip-relevant information [trip duration, data in calendar, number of passengers, hour-in-day, and points of interest (POIs)].

On the other hand, survey data are mostly collected from questionnaires and interviews, and include socio–demographics data (age, gender, occupation, and others), attitudes and psychological characteristics. This kind of data usually contains personal information; therefore,

it is often sensitive. Sensitive data not only comprises images or videos containing riders' faces, personal and identifiable information (name, address, vehicle license plate, or any other identifiable information), but also other sensitive information (including health data like permanent or temporary driver impairments, crash, and traffic violations history, or cell phone data).
Video data itself is worth mentioning separately because of its vast size and the need to extract information from the frames and processing resources needed for it. Reasonable quality video data rates produces 6-8 megabytes of data per minute which is roughly 20 gigabytes of data per vehicle per month. Video data typically comprises 80-95% of the total data collection (Sheila G. Klauer, Perez, and McClafferty, 2011). Previous projects (PROLOGUE, 2011; FOT-Net WIKI, 2015) highlighted the importance of creating a consistent format and common standards, such as decentralizing data collection, coding, and processing, to make the data format consistent between project partners. A basic off-the-shelf data acquisition system (DAS) is therefore recommended (PROLOGUE, 2011). Data collection practices in the above projects are summarized in Table 2.4 (based on the obtained references).

Table 2.4.: Summary of previous data collection practices (*source: own*)

Project	Mode	Size frequency	In-vehicle data	Survey data	Sensitive data
100-car NDS	Car	43 hrs of data	•	•	•
SeMiFOT	Car, truck	3000 hrs of data	•	•	•
INTERACTION	Car	3000 hrs of data	•	•	
2BeSafe	Car, truck, PTW		•	•	•
PROLOGUE	Car	Between 10 and 100 Hz	•	•	
SHRP2	Car	800 TB video data, 100 TB sensor data	•	•	•
SH-NDS	Car	10 to 50 Hz	•		•
ANDS	Car	60 TB	•	•	•
OBMS	Truck		•	•	
UDRIVE	Car, truck, scooter		•	•	•
Canada NDS	Car, truck	15 Hz continuous video	•	•	•
Track & Know	Car, truck, bus	1TB for one year	•		

2.2.2. Data preparation

Handling data includes aspects of data preparation. The first step of data preparation is pre-processing. This step includes different techniques such as resampling for harmonizing resolution (Victor, Bärgman, et al., 2021) and reformatting paper records (2-BE-SAFE, 2012; 2-BE-SAFE, 2017). The second step enriches the original data by adding new information (UDRIVE, 2017; Victor, Bärgman, et al., 2021; Track & Know, 2021). Data enrichment can include map data attributes by map matching (Victor, Bärgman, et al., 2021; UDRIVE, 2017; Track & Know, 2021), and other attributes such as weather information and POI (Track & Know, 2021).
Finally, synchronization of data is also necessary, especially for data coming from different sources; this task can be addressed by a custom-developed software (Victor, Bärgman, et al., 2021). Moreover, specific synchronization tasks are also required: the trip can be matched to

a driver (UDRIVE, 2017) by confirming driver ID on the first video frame. A summary of previous practices is provided in Table 2.5.

Table 2.5.: Summary of previous data preparation practices (*source: own*)

Project	Data pre-processing	Data Enrichment	Synchronization
100-car NDS	•	•	•
SeMiFOT	•	•	•
2BeSafe	•		
PROLOGUE	•		
SHRP2	•	•	•
UDRIVE	•	•	•
Track & Know	•		

2.2.3. Data storage

NDS usually require a double storage system comprising local onboard storage and a remote data storage that gathers all participants' data. Regarding onboard storage, popular means include hard drives mounted on an onboard DAS (European Commission, 2017; Dozza, Bärgman, and J. D. Lee, 2013; K.-F. Wu, Aguero-Valverde, and P. P. Jovanis, 2014), flash storage such as SD cards that are plugged into the onboard diagnostics interface (OBD II), and onboard computer (L. Fridman et al., 2019; Knoefel et al., 2018b; B. Wallace et al., 2015). For instance, Victor, Bärgman, et al. (2021) used hard drives, FOT-Net WIKI (2015) stored data through onboard Micro-SD interface, and PROLOGUE (2011) organized all operations at the local level, and there was neither standard storage nor consistent data.

The remote data storage is classified as two types, i.e., offline storage and online storage. While some projects (2-BE-SAFE, 2012; 2-BE-SAFE, 2017; UDRIVE, 2017; Track & Know, 2021) used offline storage, e.g., Track & Know (2021) recorded historical GPS data in offline storage, other projects (PROLOGUE, 2011; FOT-Net WIKI, 2015; UDRIVE, 2017; Victor, Bärgman, et al., 2021) chose the online storage system; Victor, Bärgman, et al. (2021) established an Oracle database and a database model inspired by the University of Michigan Transportation Research Institute. The remote database was arranged as a part of the Chalmers University computer system. This arrangement was also followed by UDRIVE (2017), together with the remote access to the data and possibility to analyze and annotate at a central data center. Following a similar idea, PROLOGUE transferred data from CF-cards to password-protected file server folders with only assigned scientific staff access.

When transferring data from onboard storage to remote storage, two major methods have been used. First, data can be transferred to the remote storage manually. In the Canadian NDS (Candrive study), participants met regularly with the study team to move data into the remote data storage and empty the onboard storage media in the Candrive study (B. Wallace et al., 2015). In UDRIVE, the process of transferring data meant scanning QR codes on the vehicle, data logger, and hard drive, ensuring correct data matching. Hard drives were sent from project partners across Europe to a data storage in France for collation and further processing (UDRIVE, 2017).

Another way to transfer data is through wireless networks such as Bluetooth, WLAN, and cell network transmission (PROLOGUE, 2011; 2-BE-SAFE, 2012; 2-BE-SAFE, 2017; Victor, Bärgman, et al., 2021). For example, Victor, Bärgman, et al. (2021) uploaded summary/status information via wireless 3G/GPRS, while 2-BE-SAFE (2012) transferred data from all the partners to a single server using a File Transfer Protocol. The video was also stored individually to extract individual frames on a timestamp basis (synchronized with the database data).

To meet the data query's needs, selecting the remote database's storage architecture, or software technologies, also differs between the projects. Key features comprise processing speed, file servers that deliver data to researchers' computers, and servers' links. A summary of data storage practices in the above projects is summarized in Table 2.6.

Table 2.6.: Summary of previous data storage practices (*source: own*)

Project	On-board storage	Offline storage	Online storage
100-car NDS	•	•	
SeMiFOT	•	•	
INTERACTION	•	•	•
2BeSafe	•	•	
PROLOGUE		•	•
SHRP2	•	•	•
UDRIVE		•	•
Track & Know		•	

2.2.4. Legal and ethical considerations

Besides data collection, storage, and access, legal and ethical considerations are crucial for successful NDS experiments, and for their viability in the first place. This section presents practices that were conducted in previous projects, focusing on data sharing, data protection, and data maintenance after the project lifetime, along with ethical and legal considerations, where applicable. In general, the naturalistic driving study project activities conform to national and international laws. In European projects, particular attention is paid to the EU Regulation 2016/679, or GDPR, which came in effect from 25 May 2018 (European Parliament and Council of European Union, Regulation, 2016). In addition, project partners usually have their own ethical committees (based on external experts) looking after ethical issues in relation with conducting the experiments (Track & Know, 2021).

Practical implementation strategies have been followed in different projects and are presented in this section. Video data, geo–data, and questionnaires data, all contain personal data and are subject to the European Directives (T. A. Dingus et al., 2006). Pseudonymization/anonymization of data is usually done to protect participants' anonymity before transferring the data to the common server – that is when drivers' name and other identifiable information (e.g., address) are separated from the data and replaced with a unique identifier(2-BE-SAFE, 2012; SHRP 2, 2013; 2-BE-SAFE, 2017; Track & Know, 2021).

Project partners are responsible for managing participants' confidentiality and for retaining the ability to identify participants if required and only the project leader may have access to this relevant information (2-BE-SAFE, 2012; 2-BE-SAFE, 2017; Track & Know, 2021). In addition, the first and last minute of each journey may be deleted so that participants cannot be identified by the data alone (UDRIVE, 2017). While this procedure implies some data loss, it ensures that participants' home addresses (among others) are not identifiable.

Once the collected data are copied to an external platform, the on-board data may be deleted from the experimental vehicle's hard drive (T. A. Dingus et al., 2006). All personal data may be destroyed once they are no longer needed for analysis. Alternatively, the data may be destroyed at the end of the study period at the latest (2-BE-SAFE, 2012; 2-BE-SAFE, 2017). Non-personal data may be kept beyond the period of the study if they are of value to partner institutions in further work and if it is agreed that the data could be held. In such cases, the data may be made available to all partners, who shared equal intellectual property rights, regardless of the nationality of the source data (2-BE-SAFE, 2012; 2-BE-SAFE, 2017). The data collected within the project may be available for further research after the project for partners and for third parties, with certain limitations to adhere to the privacy of the participants (UDRIVE, 2017).

In NDS, legal, ethical, and logistical issues could arise if participants drive their equipped cars to another country for any reasons such as holidays (UDRIVE, 2017). This may ultimately lead to the loss of big portions of the data due to complications with the equipment when crossing borders. In addition, if the driver in question is not a participant, but someone who drives this vehicle incidentally, the trip should be deleted to protect the privacy of non-participants (UDRIVE, 2017). Overall, a data protection officer (DPO) must ensure that data collection and processing within the scope of the project, are carried out according to the international and national legislations (Track & Know, 2021). A summary of legal and ethical considerations in previous NDS projects is presented in Table 2.7.

Table 2.7.: Summary of previous legal and ethical considerations (*source: own*)

Project	Legal protocols	Anonymization	Disclosure permission	Access restriction
100-car NDS	•	•	•	•
SeMiFOT		•		•
2BeSafe	•		•	•
SHRP2	•	•	•	•
ANDS	•	•	•	
UDRIVE	•	•		•
Track & Know	•	•	•	•

2.2.5. Lessons learned and proposed solutions

In this section, data handling aspects for selected projects have been reviewed, focusing on: data collection, data preparation, data storage, and legal and ethical issues related to NDS data. The lessons learned from these projects are summarized along the following main points:

Data Collection. A basic, relatively simple, and cheap off-the-shelf data acquisition system (e.g., accelerometer) provides very useful data for many research questions. However, the reliability and validity of the identified safety–related events (e.g., false alarms, missed events) must be carefully checked. For projects that are implemented in multiple countries, data should be collected using a common DAS for all partners and following the same protocols and standards. In addition, it is more practical to employ only certain vehicle types for data collection as the collected data may differ for different vehicle models and the respective sensor setup. This also reduces the burden of installation and de–installation of sensors in each vehicle. Finally, it is recommended to centralize the responsibilities in terms of coding, processing, and analyses, in order to create a consistent dataset.

Data Preparation. Prior to storage, the collected data should be pre–processed so that the stored data is well–structured for analysis without further complexities for different partners involved in the project. This includes data quality procedures (data cleaning, missing data, inconsistent data, erroneous data due to calibration issues), but also already at this stage, data pseudonymization; this includes for instance dealing with geo–data, to not hinder participants' privacy. Data (vehicle and survey data) need to be pseudonymized before being uploaded to the online storage server. Moreover, questionnaire and survey data, need to be uniformly re-coded. Also, advanced video processing techniques can increase the efficiency of data storage since video data result in most of the collected data's volume within naturalistic driving studies. Finally, the collected data may be enriched by external data sources such as digital maps, roadway engineering attributes, traffic characteristics, climatic data, and questionnaires.

Data Storage. Two types of storage can be of use: on-board storage and remote storage (online and offline). Manual transmission of vehicle data from local devices should be avoided (e.g., hard drives, USB drivers, or SD cards) since it imposes extra burden on participants, resulting in the reluctance to participate and in data loss (very obtrusive method, which reminds participants of the nature of the experiments). Instead, data should be transferred automatically for example using wireless networks, such as Bluetooth, WLAN, or cell network transmission. For files that still need manual extraction and/or transfer (e.g., questionnaire data), the hard copy of the data should be stored after transforming it to the electronic version.

Data should be stored in open formats so that all project partners can have access to the data. More importantly, the data should be well defined and understandable; this is in general achieved through a clear data management plan, which defines datasets, variables within each dataset, and the partner (party) generating each dataset. Furthermore, video files should be stored separately but linked with the rest of the data so that they can be retrieved in synchronization with the database. A systematic back-up scheme is also required to prevent loss of data. The backup strategy should be based on "acceptable downtime" and would depend on the time it would take to recover data and on the acceptable amount of lost data.

Finally, the processing speed and the connection to database servers are important data storage architecture considerations to be aware of. The data could be stored in an open standard file format such as JSON, but could be converted to other standard formats if required, since converter libraries exist in all popular programming languages.

Legal and ethical considerations. As a general guideline, national and international data protection regulations (e.g., European-GDPR) should be adopted for protecting personal data in naturalistic driving studies. A few legal and ethical considerations are as follows:

1. The consent of participants is needed for collecting, storing, and using or processing their data.

2. Sharing the data to third parties requires the consent of involved partners and can only be granted upon approval of relevant committees (ethical committee, DPO).

3. Data should be pseudonymized before being shared and uploaded to a common central server. The link between the unique identifier and participants' personal information should only be available to the partners collecting that data in the first place and would need to be stored separately from the rest of the data.

4. The first and the last minute(s) of driving in each trip may be deleted to avoid any possible relation with sensitive information such as destinations with religious or political implications. Additional examples of sensitive information are elaborated by the European Commission (2019).

5. Careful consideration must be given to regulations across all possible countries of involvement as driving may occur across multiple countries. This includes cases in which the driver in question is not a participant, but someone who drives the vehicle occasionally, who have not given his or her consent to having his or her data collected.

6. Protocols must be defined for treating personal and sensitive data after the NDS end (beyond the project timeline).

Existing Gaps and Proposed Solutions

While valuable insights have been gathered through the analysis of previous NDS, an identified gap has been identified; namely, the lack of comprehensive guidelines for data handling that can be made accessible for different partners involved in similar studies. This means, there is a need to map out these lessons learned into standard protocols which could serve as a blueprint of methods to be followed in the implementation of data handling for similar (NDS) studies. A framework for data handling should therefore be developed aiming at drawing methods based on the findings and lessons learned from previous projects.

3. Methodology

This chapter presents the methods used for the completion of the doctoral work reflected in this dissertation and is structured across three main sections. In the first one (Section 3.1), experimental design methods are given, including considerations for driving simulator studies (Section 3.1.1) and field trials (Section 3.1.2). The second section presents analysis methods (Section 3.2), including an overview on factor analysis (Section 3.2.1), discrete choice models (Section 3.2.2), and panel data models (Section 3.2.3). Finally, the third section presents tools for understanding and modeling technology acceptance (Section 3.3)

3.1. Experimental design

3.1.1. Driving simulator experimental design

Designing driving simulator experiments is time–consuming and requires preparation. It is therefore crucial to keep in mind design principles before any experimental design, which can be drawn from the experience of previous research and recommendations. In the below paragraphs, an overview of design principles for driving simulator experiments is given, based on the guidelines from Fisher et al. (2011), and as described in Fran Pilkington-Cheney et al. (2020). Considerations for the experimental design can be summarized as follows:

1. **Definition of outcomes, predictors and hypothesis.** These are defined depending on the research question, along with a set of hypotheses. The outcomes in a driving simulator experiment may be categorical (abnormal/normal driving, warning/no warning) or continuous (e.g. headway distance, speed, acceleration, deceleration). Moreover, outcomes can be objective or subjective (as was indicated in Figure 2.2). Predictors, on the other hand, may be individual-specific characteristics (e.g. demographics, attitudes, etc.) or may be experimental factors (e.g. road layout, environmental conditions, and interventions). Whether a factor is an outcome, or a predictor highly depends on the research questions and objectives of the experiment. Therefore, it is essential to define certain hypotheses that link the outcomes and predictors with each other. The study hypothesis is usually formulated in terms of a null hypothesis (H_0) and an alternative hypothesis (H_1) and the aim is to reject that null hypothesis using the data collected within the driving simulator experiments.

2. **Sample size and power.** Sample size is directly related to the statistical power of the experiment, that is, how strongly the null hypothesis can be rejected assuming

that the alternative hypothesis is true (X. Wang and Fu, 2019). This depends on the hypothesis and in turn on the type of the statistical test being used. The statistical power calculations, however, are more complicated (Dupont and Plummer Jr, 1990) and depend on three general aspects of the experiment: sample information (mean and standard deviation and common statistical tests, such as t-tests, Chi-square tests), sample size and the required statistical significance. Calculating the sample size therefore requires setting up the other two aspects and so selecting a sample size could be an iterative process where the starting point could be based on historical normative values, studies from other participant populations, and small pilot studies.

3. **Full/fractional factorial design.** Factorial experiments, in contrast to one-factor-at-a-time (OFAT) experiments, aim to investigate the relationship between one (or more) outcomes with multiple predictors (factors) at the same time. More efficient than OFAT designs, factorial designs can investigate the differential effects of one predictor across different levels of other predictors. Moreover, factorial designs investigate the effects of multiple factors with no additional costs, leading to conclusions across wider range of experimental conditions.

   A full factorial design includes all combinations of predictors at their discrete possible values or "levels". As expected, the size of full factorial design experiments increases exponentially with a high number of predictors which makes the experiment impractical and cumbersome. Among all combinations of a full factorial design, many are redundant and may not add new information to the experiment. An alternative design is a fractional factorial design (Box and Hunter, 1961; Fisher et al., 2011), taking into account only a part (fraction) of all combinations of predictors at their levels in the full factorial design. Combinations that can be included in the fractional factorial design should be balanced and orthogonal (Mukerjee, 1980; Kacker, Lagergren, and Filliben, 1991). In other words, observations in the sample should be evenly distributed (balanced) across combinations and the effects of any factor should balance out (sum to zero) across the effects of the other factors (orthogonal).

   However, it is important to note that there may be more than one orthogonal combination. The number of generators (effects or interactions that are not orthogonal) is set by the designer and is usually based on special requirements of the study (e.g. limitation of resources or sample size).

4. **Within-participant or between-participant design.** Another important consideration when designing driving simulator experiments is to define whether one participant drives different conditions (e.g. with and without warnings) and the outcome variables are compared within participants, or all participants are split randomly and some participants drive one condition (e.g. with warning) and the rest of the participants drive another condition (e.g. without warning) and the outcome variables are compared between participants (Fisher et al., 2011). The former design is referred to as within-participant and the latter design as between-participant. The main advantage of the within-participant design over the between-participant design is that it has a high

statistical power because each participant serves as their own control. The statistical power for within-participant designs are high enough even if the entire sample is not used. However, the within-participant design has a few disadvantages over the between-participant design:

- Some variables are, by definition, within-participant; e.g. gender. It may also not be practical or ethical to change the levels of a variable (e.g. weight) for a participant during the experiment.
- It may be subject to contamination (e.g. carryover effects, learning effect) which can influence the conclusions.
- It is often more difficult to implement because external devices should be mounted and dismounted from the simulator during the same drive.

5. **Assignment of scenarios to drives.** A driving simulator experiment often consists of various scenarios, each of which can have different outcomes, predictors, and hypotheses. Therefore, knowing whether to allocate each scenario to a distinct drive, or multiple scenarios within the same drive, is essential. It can create a trade–off between efficiency and practical difficulty of the experiments. Having one scenario in one drive is simpler to implement, and reduces the likelihood of contamination and learning effects. On the other hand, having multiple scenarios in one drive is more efficient, may reduce the overall number of trials, particularly in big studies, and can increase the within-participant variability and consequently the statistical power of the study. Therefore, there is no rule of thumb for choosing whether to include single or multiple scenarios in one drive. A pilot study may be helpful in making this decision.

6. **Order of drives and learning effects**. The order of scenarios and events must be randomized among the participants and during the trials. These are two important concerns that should be accounted for in experimental design. Order effect results from changing the order of events and scenarios among participants (Shaughnessy, E. B. Zechmeister, and J. S. Zechmeister, 2000). These are especially important in within-participant designs where participants drive all conditions. Learning effect, on the other hand, is referred to as the change in driving behavior (or improvement) resulting from repeating the same event/scenario in the trial (Fisher et al., 2011). Therefore (because of both effects), the order of drives should be random across participants and across time. Participants should be assigned with an identification number and selected based on a randomized selection of those numbers. Similarly, the drives with different scenarios should be randomized in terms of the time of implementation; otherwise, the results may be biased. However, randomizing all the scenario drives completed by a participant may not be possible without baseline data from that participant.

7. **Simulation sickness and duration of drives.** Simulation sickness is the ill feeling, reported in both fixed and motion-based driving simulators (M. Draper et al., 1997; Ehrlich, 1997; M. H. Draper et al., 2001). Simulation sickness can result in severe symptoms including eye strain, headache, nausea, and vomiting, and can influence

driving behavior and performance, therefore invalidating some results. Participants may lose their motivation and ability to concentrate, avoid tasks that are found disturbing, or even modify their behavior to reduce sickness symptoms. To mitigate it, it is recommended that scenarios have minimal rapid change in direction and acceleration. Wider curves and fewer roadside objects may also help reducing simulator sickness among participants. The total duration of the simulation should not exceed two hours and the duration of each drive should not exceed one hour, with shorter drives for more demanding scenarios. Although there are no set of rules for drive duration, the general practice is to set it between 5 and 25 minutes, with a break of 10 minutes in between. It has been shown that simulator sickness increases with the drive duration in one trial but decreases with successive trials in multiple sessions (Kennedy, Stanney, and Dunlap, 2000). Designing a few practice drives prior to the main drive may help reduce the simulator sickness effect; however, these can result in learning effects. Overall, a higher fidelity of the driving simulator to the real–world environment contributes substantially to the mitigation of simulator sickness. The latter has also been shown to correlate with individual characteristics (including health status); therefore, screening participants during the trials can help avoid sickness for individuals who are particularly susceptible to it, including those with fatigue or sleep loss, upset stomach, head colds, ear infections, ear blockages, pregnancy, upper respiratory illness, or those or who have recently taken medications or alcohol.

8. **Confounding effects and effect modification.** A confounding effect in a driving simulator experiment is referred to as the circumstances in which the association between an outcome and a predictor is due to a third external factor, the confounder. For example, the association between abnormal driving and lane deviation may be primarily due to long driving hours. Characteristics for a variable to be considered a confounder has been defined in Fisher et al. (2011). Neglecting confounding can result in incorrect sources of predictors, and perhaps more importantly, not being able to replicate the findings. Thus, it may be more helpful to hypothesize a few confounders and effect modifiers, and to test these effects during the experiments. Nevertheless, confounding effects and effect modification may be addressed in the analysis phase, if they cannot be addressed in the design phase.

3.1.2. Considerations for field trials

When planning for naturalistic driving experiments, it is important to consider learnings from previous studies and projects. Chapter 2 previously highlighted learnings for developing a data—knowledge cycle for driving behavior modeling, with a particular focus on data handling for naturalistic driving experiments. Further, the FESTA handbook (*FESTA Handbook* 2018) highlights several aspects to consider when planning field trials. Based on those, and considering an experiment that is to be conducted in various countries, covering different modes of transport, a set of guidelines can be developed (also presented in Fran Pilkington-Cheney et al. (2020)), that can be summarized as follows (and in no particular order):

1. **Plan of approach.** Developing checklists alongside detailed plans can help in avoiding delays and saving resources. A pilot plan would aim at describing all procedures, necessary forms, participant-related and vehicle-related documents, instruction manuals and guidelines to instrument vehicles, contact participants, etc. Before the start of the actual field trials, the pilot plan can be adjusted in case any issues were encountered during the pilot phase.

2. **Participant recruitment.** The recruitment process takes a long time and therefore should be well–planned, for it to be successful. Recruitment should start early on, to allow time to meet adequate numbers and to provide more time in case of delays. It is also recommended that all procedures, and needed documents are ready and translated into the local language of the field trial location before starting the recruitment process; these steps can avoid delays that can lead to participant dropouts.

   A screening questionnaire can ensure that the defined participant selection criteria are met. For instance, participants should be selected so that they are within a maximum one-hour travel radius from the field trial base. For larger distances, it becomes quite cumbersome to solve technical problems concerning the data collection system. Barriers to participation can include the duration of the trial experiment (several months) followed by the fear that participants' vehicles might be damaged due to the installation of the equipment. This can be overcome by selecting sufficient and efficient recruitment channels and being transparent about the field trial, which can make people more receptive to participate.

3. **For professional drives.** The participant recruitment for professional drivers can be difficult because there are different stakeholders involved that need to agree to participate. The main contact person of the fleet, the company management, the union and the professional driver themselves have to agree to join the field trial. Unions should be approached from the start and should be informed about all aspects of the field trial to avoid delays; unions need to approve changes in the worker's working environment (such the installation of monitoring equipment). It is recommended that fleet owners inform the field trial responsible about their driving schedules so that it is known when a driver change takes place. This will also help with driver identification.

   To encourage participation, the value of safe driving conditions and contribution to safe traffic, positive company image, etc., can be an incentive for companies to participate.

   Finally, questionnaires need to be adjusted for professional drivers as their driving experience and behavior differs significantly from non-professional drivers. Professional drivers might be more willing to participate if they also receive an incentive. However, this is something that the fleet manager should decide.

4. **Participant dropout and incentives.** To avoid dropouts, it is important to keep participants well-informed about the field trials and stress that their contribution is important; being transparent about the study conditions should already start during recruitment and participant briefing. Moreover, it is essential to comply with the starting and end

dates communicated to participants. This can be done by developing a realistic and detailed plan of action for the experiment. By means of this plan of action, all necessary steps and issues prior to and during the experiment are identified with the aim of avoiding delays that can result in participant dropouts. It is also important to create a reserve pool of participants during the recruitment process; these participants can then easily replace the initial participants that may drop out during the experiment.

In defining the right incentive strategy for field trials, several aspects should be considered. First, the incentive strategy (amount, type of payment and payment periods) must be specified in the participant agreement/consent form to avoid discussion afterwards. The incentive needs to be high enough; otherwise, if the incentive is not high enough, for instance if the (monetary) benefit is not in line (lower than) with the duration of the experiment, it will not motivate potential participants. Incremental incentive payments are recommended to reduce the dropout rate and encourage participants to be committed to stay in the trials until completion. A dropout budget could be implemented to recruit back-up participants during all field trial stages. This dropout budget ensures that participation can still be appealing to the back-up participants even if they enrol in the later stages of the trials.

The incentives need to be managed locally by the responsible field trial partners as legal aspects for receiving incentives may differ across countries. For example, depending on national legislation (income tax regulations), it might be necessary to pay the incentive by vouchers. Participants should be informed in advance if the received incentives need to be reported in their income tax declaration. This should be mentioned in the participant agreement/consent form.

5. **Vehicle instrumentation.** Certain aspects should also be considered regarding the equipment that will be installed in the vehicles. Essentially, all equipment should be checked before installation; spare parts should be available in case of equipment failure. Finally, the planning and organization of equipment installation should be carefully considered, ensuring that there is enough personnel to handle the vehicles and that a limited number of vehicles are installed/de–installed at once, to help with installers' coping capacity.

6. **Participant handling.** A good participant handling and support is essential to avoid dropouts. A clear procedure should be in place to handle participant complaints. For this, a helpline by means of having a dedicated e-mail address and/or telephone number will be developed. This helpline should be monitored regularly so that participant issues and complaints can be dealt with as soon as possible (e.g., within two working days). Furthermore, researchers can be assigned to exclusively deal with solving participant issues. The assigned person can differ according to the specific issues (general issue, ethical/legal issue, problems with the data collection equipment etc.). Moreover, it is important to maintain informal contacts with participants. In case of suspected failure in data logging, participants can be contacted to check if the equipment still works. Participants should be instructed to contact the researchers in case of specific

circumstances such as damage to the vehicle or equipment, not using the vehicle for long time due to illness or holidays, change in driving patterns due to job change, etc.

7. **Ethical and legal issues.** Issues that should be considered are the approval of the competent national authorities for data protection (when necessary/applicable). Participant consent forms are essential as they detail the conditions of the experiments, notably the part regarding the data collection, use, and processing. For instance, a passage can detail that the data of participants who have not signed the participant consent form (i.e., second driver of a vehicle) would not be collected during the study.

   Insurance, for instance is one issue that should be carefully considered: an insurance for the equipment, for the installation, but also an insurance to cover third party liability, and to compensate participants for damages caused to their vehicles by the installed equipment, or a potential claim that participants might make against researchers in case of an accident (blaming the experiments as a reason for their accident).

3.2. Analysis methods

3.2.1. Factor analysis

Factor analysis is a statistical method that aims to describe a set of observed variables in terms of a lower number of latent (unobserved) factors, by looking at their maximum common variability and the proportion of the overall dataset variance they explain. In transportation data analysis, this method has been used to reduce the number of variables (Washington, Karlaftis, and Mannering, 2010).

There are two types of factor analysis: the Exploratory Factor Analysis (EFA) and the Confirmatory Factor Analysis (CFA). The former is a subset of structural equation modeling and aims, as its name indicates, to explore latent factors behind the observed variables, to better reveal the structure and patterns of the data. The latter goes from an already existing theory and hypothesis on the structure and aims at verifying it. In the following part, the focus is rather on EFA as an exploratory approach, as it can be more useful in revealing latent constructs behind a set of statements and attitudes, often resulting from questionnaire data.

For a given observation and a set of p random observable variables, $x_1,...,x_p$ with means $\mu_1,...,\mu_p$ respectively, the latent unobserved factors $F_1,...,F_k$ can be found by solving the set of linear equations:

$$x_i - \mu_i = l_{i1}F_1 + l_{ik}F_k + \epsilon_i \tag{3.1}$$

where,

- l_{ij} is constant representing the factor loading of factor j in variable i
- i $\in$ 1,...,p
- j $\in$ 1,... ,k

- k is the number of unobserved or latent factors in the factor analysis
- k < p
- ϵ_i is the random error term associated with x_i, with mean zero and finite variance

In matrix notation, this equation is expressed as follows:

$$(X - \mu)_{p\times 1} = L_{p\times k}F_{k\times 1} + \epsilon_{p\times 1} \tag{3.2}$$

For n observations, the above matrix notation is translated to the below, where $L_{p\times k}$ is constant across all observations:

$$(X - \mu)_{p\times n} = L_{p\times k}F_{k\times n} + \epsilon_{p\times n} \tag{3.3}$$

The solution for these equations would give the factor and loading matrices F and L, respectively. As there are $p + k$ unknown but only p equations, some restrictions are needed. In an orthogonal model, the factors and their loading are unique, and the following assumptions are satisfied:

- F and ϵ are independent
- E(F) = 0
- COV(F) = I, the identity matrix
- COV(ϵ) = Ψ, the diagonal matrix

EFA has been used in several studies focusing on public transit user satisfaction (Tyrinopoulos and Antoniou, 2008), vehicle sharing adoption (Efthymiou, Antoniou, and Waddell, 2013) or technology acceptance for several concepts including e-commerce and e-shopping (Ahn, Ryu, and Han, 2004; Shih, 2004). It is often used in combination with other statistical models like behavioral modeling, or structural equation modeling (Van der Heijden, 2004). A study on the adoption of vehicle sharing system used factor analysis to extract the perceived car and bike ownership characteristics in order to better understand latent correlation between them. The reduced number of variables helped build ordered logit models to better predict vehicle-sharing adoption (Efthymiou, Antoniou, and Waddell, 2013).

EFA consists of several essential steps. First, the factors extraction method is chosen. After that, the preferred number of factors to be retained is determined according to different methods. Then, a rotation method is chosen and applied to allow a better visualization of the retained factors. Factor loadings are thereafter extracted for each factor. Finally, factor scores are computed from the obtained loads (Costello and Osborne, 2005).

The most common extraction method is the maximum likelihood estimation (MLE) which assumes that the data is relatively normally distributed (Costello and Osborne, 2005). Otherwise, principle axis factors is recommended. However, MLE is overall better as it doesn't inflate the results since it still explains the shared variance, whereas the principle axis factors method assigns all communalities as one. The recommended number of factors usually follows the Kaiser-Guttman criterion which retains the variables with an eigenvalue greater than one (H. F. Kaiser, 1960). Other methods include the scree test, Velicer's MAP criteria, and the parallel analysis method (Velicer and Jackson, 1990; Hayton, Allen, and Scarpello, 2004; Costello and Osborne, 2005). The former is usually preferred as it is available in most software packages.

The rotation method depends on the factors' correlation. If the factors are not correlated, orthogonal methods are applied; most commonly *varimax* is utilized. Otherwise, oblique methods are used, the most common one being *oblimin*. There are also other rotation methods beyond those listed above, and the package *GPArotation* in R offers many options for that (Bernaards and Jennrich, 2005). After rotation, factor loadings are obtained. These indicate the loading or weight of each variable in a specific factor. A high factor loading means that the variable highly explains the variance in the extracted factor. The variables that do not or poorly load in all the factors are considered less important in explaining the overall variance of the variables and are not retained as explanatory factors in the dataset's architecture. Finally, factor scores are computed, taking into account the factor loadings calculated, by computing for example a weighted average of these.

3.2.2. Discrete choice models

Discrete choice modeling is a widely used method in revealing user preferences for a given choice and uses the principle of utility maximization. This means that each individual is assumed to choose the alternative having the highest utility, which in turn is based on attributes related to the alternative and the decision–maker (Ben-Akiva, Lerman, and Lerman, 1985).

For a an alternative i and an individual q, the utility is a combination of a systematic element V_{iq} and a random component ϵ_{iq} (Louviere, Hensher, and Swait, 2000), as shown in Equation 3.4 below:

$$U_{iq} = V_{iq} + \epsilon_{iq} \tag{3.4}$$

where,

- U_{iq} is the utility of alternative i for individual q
- V_{iq} is the systematic component of alternative i for individual q
- ϵ_{iq} is the random error component associated with V_{iq}

V_{iq} is a combination of components exclusively associated with the attributes of the alternative (varying for the same individual across different alternatives), of the decision-maker (constant for the same individual across different alternatives), and the interactions between attributes of the alternative and characteristics of the decision-maker. The systematic component V_{iq} also includes an alternative-specific constant for the given alternative i (Koppelman and Bhat, 2006).

For a given utility, the alternative-specific constant (ASC) captures the effect of factors that are not part of the model. By adding this constant, the unobserved or remaining error term is bound to a mean of zero (Train, 2009). As only the differences in utility matters, one alternative can be normalized to zero by setting its ASC to zero. Therefore, for i alternatives, the model can at most have i-1 ASCs. V_{iq} can be written in terms of its explanatory observed variables or attributes (Ortuzar and Willumsen, 2011), as follows:

$$V_{iq} = \beta_{1i} X_{1iq} + \beta_{2i} X_{2iq} + \cdots + \beta_{ki} X_{kiq} \tag{3.5}$$

where,

- $\beta_{1i}, \beta_{2i}, \cdots \beta_{ki}$ are the unknown parameters to be estimated, that are constant for the individual but may vary across alternatives.
- $X_{1iq}, X_{2iq}, \cdots X_{kiq}$ are the k independent variables including all attributes of alternative i for individual q: decision-maker and alternative related.

Individual q will choose alternative i over j if and only if the utility of i is greater than that of j; in other terms, if $U_{iq} > U_{jq}$.

This leads to the following equations (Louviere, Hensher, and Swait, 2000):

$$V_{iq} + \epsilon_{iq} > V_{jq} + \epsilon_{jq} \tag{3.6}$$

$$V_{iq} - V_{jq} > \epsilon_{jq} - \epsilon_{iq} \tag{3.7}$$

The difference between the error terms cannot be calculated, but rather the probability that $V_{iq} - V_{jq}$ is greater than that of ϵ_{jq} - ϵ_{iq} (Louviere, Hensher, and Swait, 2000). A random utility model is therefore generated due to the random error term, which is assumed to follow a given probability distribution. In other terms, the probability P_{iq} that individual q chooses alternative i is as follows (Ben-Akiva, Lerman, and Lerman, 1985):

$$P_{iq} = P(U_{iq} \geq U_{jq}) \tag{3.8}$$

Considering a specific probability distribution for the error term, the equation above can be solved and the β coefficients can be estimated using MLE (Ben-Akiva, Lerman, and Lerman, 1985).

Note: To add a qualitative independent variable, it is important to set one of the levels of this variable as a base case, and thereafter add the other levels as binary variables (0 or 1). Therefore, for k levels of a given attribute, at most k-1 binary variables can be added to the model; otherwise, the variables would be redundant.

Depending on the probability distribution of the error term, there are different types of discrete choice models (Ben-Akiva, Lerman, and Lerman, 1985). A common assumption that the error term is normally distributed (Koppelman and Bhat, 2006) leads to the formulation of probit models. However since they can be difficult to solve, logit models based on a logistic distribution of the error term are more commonly used. Logistic regression models are commonly used in regression analysis, where independent variables are explored in terms of their relation to the dependent variables they explain (Hosmer Jr, Lemeshow, and Sturdivant, 2013). In logit models, the discrete outcome variable is binary and the resulting model is called binary logit model. Several other models following logistic regression are used in practice, and explained in the following section.

Multinomial Logit Models (MNL):
They are logit models with more than two dependent variables or two unordered outcomes. The main assumptions followed in this model are the Independence-from-Irrelevant Alternatives (IIA) and Independent and Identically Distributed (IID) variables. IIA states that choosing one alternative over the other does not depend or is not affected by the presence or absence of other alternatives (Louviere, Hensher, and Swait, 2000). IIA also means that for different alternatives, the random error terms ϵ_{iq} are independent and identically distributed. Based on the above properties and the extreme value type one (EV1) distribution, the multinomial logit model is translated to the following (Train, 2009) equation:

$$P_{iq} = \frac{e^{Vjq}}{\sum_{j=1}^{J} e^{Vjq}} \tag{3.9}$$

where,

- P_{iq} is the probability of choosing alternative i by individual q
- V_{iq} is the systematic component of the utility of alternative i for individual q
- V_{jq} is the systematic component of the utility of alternative j for individual q

Multinomial logit models have been widely used in transportation research. For instance, MNL models have been used in pedestrian crossing behavioral analysis (Kadali and Vedagiri, 2012) or long ago in passengers' choices for airports(Ashford and Benchemam, 1987). In air mobility, MNL models were used to model VTOLs as touristic mobility modes in Sicily, Italy (Amoroso et al., 2012).

There are however several limitations to the MNL models. Often, their basic assumptions are violated due to the nature of the dependent variable. For instance, if outcomes are ordered or in case alternatives share some similarities, other models could be used, such as ordered or nested models.

Ordered Logit Models (OLM):
They are extensions of the logistic regression models and are applied to more than two ordered responses or dependent variables (McCullagh, 1980). They are mostly applied in user preference studies, where respondents are asked to rate their satisfaction in a scaled outcome, often ranked in a Likert scale (Likert, 1932). OLMs were used to model user satisfaction of transit systems in Athens, Greece (Tyrinopoulos and Antoniou, 2008), or to model the adoption of new mobility patterns, such as vehicle-sharing (Efthymiou, Antoniou, and Waddell, 2013).

For ordered outcomes, OLMs can relax the IIA assumption (Ben-Akiva, Lerman, and Lerman, 1985). In such models, threshold values, also known as intercepts or cutoff values, are estimated between the different ordered outcomes. The order of an observation can be modeled by defining a latent variable Z, corresponding to the exact unobserved dependent variable, represented as follows (Washington, Karlaftis, and Mannering, 2010):

$$Z = \beta X + \epsilon \tag{3.10}$$

where,

- X is the vector of independent variables
- β is the vector of parameters to estimate
- ϵ is the error term

Although the exact value of Z cannot be determined, an estimate of the categories of responses is found, based on the observed ordered data y (stated dependent variable):

$$\begin{aligned} y &= 1 \text{ if } z \leq \mu_0 \\ y &= 2 \text{ if } z \leq \mu_0 \leq \mu_1 \\ y &= 3 \text{ if } z \leq \mu_1 \leq \mu_2 \\ y &= \cdots \\ y &= I \text{ if } z \geq \mu_{I-1} \end{aligned}$$

where,

- μ are the estimate parameters corresponding to the cutoff or threshold values for the different ordered outcomes
- I is the highest ordered outcome

OLMs result in estimates for both β and μ parameters. For each individual, the probability of the I ordered outcomes is estimated assuming specific probability distributions (Washington, Karlaftis, and Mannering, 2010). For two response levels, the model is simply the binary logit model (Harrell, 2015).

3.2.3. Panel data models

Panel datasets may have the capacity of capturing individual (or household as individual) effects, time effects, or the combined effects of both household and time. These effects are either fixed or random. A fixed–effect model assumes differences in intercepts (constants) across households or time periods, whereas a random–effect model explores differences in error variances. The random–effect model estimates variance components for groups and error, assuming the same intercept and slopes. The difference among groups (household or time periods) lies in the variance of the error term. A one-way model includes only one set of dummy variables (e.g., household), while a two way model considers two sets of dummy variables (the combined effect of both household and time (H. M. Park, 2015). The fixed household or time effect model can be formulated as follows:

$$y_{it} = \alpha_i + \beta x_{it} + e_{it}, \qquad \text{where } e_{it} \backsim IID(0, \sigma_e^2) \tag{3.11}$$

and,

- y_{it} is the dependent variable (of household i, in time t)
- α_i is the household specific constant
- x_{it} is the explanatory variable
- β is the coefficient associated with the explanatory variable
- e_{it} is the error term.

The basic formulation of the model assumes that differences across units can be captured in differences in the constant term (α_i); thus, in the above formula, each α_i is an unknown parameter to be estimated. The model usually refers to the least square dummy variable model (LSDV). To see the combined effects of both time and household, the LSDV can be extended to include a time–specific effect as well. One way to formulate the extended model is simply to add the time effect as follows:

$$y_{it} = \alpha_i + \gamma_t + \beta x_{it} + e_{it} \tag{3.12}$$

where, γ_t = time specific constant.

In the case of a fixed–effect model, if we are interested in differences across groups (households), we can test the hypothesis in such a way that the constant terms are all equal to zero. This hypothesis can be tested using the F test. If the null hypothesis is rejected, we may conclude that the fixed group effect model is better than the pooled or ordinary least square (OLS) model; i.e., there is a variation (a fixed effect) of the dependent variable across groups (household or time). In other settings, it might be more appropriate to view the individual–specific constant term (v_i) as randomly distributed across cross-sectional units (Greene, 2000). The random household or time effect model can be then formulated as follows:

$$y_{it} = \alpha + \beta x_{it} + (v_i + e_{it}), \qquad \text{where } e_{it} \backsim IID(0, \sigma_e^2) \text{ and } v_i \backsim IID(0, \sigma_v^2) \tag{3.13}$$

3.3. Technology acceptance models

Understanding societal perceptions and user acceptance of a certain technology is always key before its successful implementation. In understanding or better representing the acceptance of specific technologies, various models have been used in research; perhaps the most renown remains the technology acceptance model (TAM) by F. D. Davis, Bagozzi, and Warshaw (1989), initially developed to investigate technology use of information systems, particularly computer technology, in which the correlation between the intention to use and actual usage was measured. The main aim of the model is to present a framework for modeling users' acceptance in terms of factors that influence their decisions in using the technology. This model is based on two main constructs: the perceived usefulness (PU) and the perceived ease of use (PEU), where PEU reinforces PU. The former is the extent to which the user believes the technology use would enhance his or her job performance, whereas the latter is the degree to which using the technology requires effort. Both factors determine the user attitude towards using the system, which in turn determine the behavioral intention (BI) to use the system, and then the actual system use. This model also includes external variables, which affect the defined constructs.

Various versions have been then extended based on this model, among others, TAM2 (Venkatesh and F. D. Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, et al., 2003), and a later revision into TAM3 (Venkatesh and Bala, 2008). As mentioned in Al Haddad, Chaniotakis, et al. (2020), the role of moderating factors (factors impacting adoption and reducing the limitations of the model's explanatory power) has been found crucial (H. Sun and P. Zhang, 2006) in technology acceptance models; for instance, the moderating effects of gender and self–efficacy in the context of mobile payment adoption (Riad et al., 2014).

In better understanding vehicle technologies, and as the focus of this dissertation is on driving behavior modeling, experiments can be conducted, such as driving simulator or on-road studies, in which the acceptance of modern in–vehicle technologies can be tested, using the premises of the technology acceptance model. Based on questionnaires, assessment, but also drivers' behavior, the acceptance of such systems can be tested. Several hypotheses can be tested along the lines of the traditional TAM, which are depicted in Figure 3.1, and denoted as H_1, H_2, and H_3 (hypotheses 1, 2, and 3, respectively).

These hypotheses aim to test the following:

1. H_1: BI = f(PU, PEU). This means that the behavioral intention to use the technology (for instance a certain ADAS) is a function of its perceived usefulness and perceived ease of use. In particular, for this dissertation, the behavioral intention to use the system refers to the intention to continue using the in–vehicle system if given the choice.

2. H_2: PU = f(PEU, external variables). This means that the system's perceived usefulness is a function of its perceived ease of use and of external variables. External variables here could be gender, other demographics, ADAS use, or other perceptions towards ADAS and other driving habits or driving history.

3. H_3: PEU = f(external variables). This means that the system's perceived ease of use is a function of external variables.

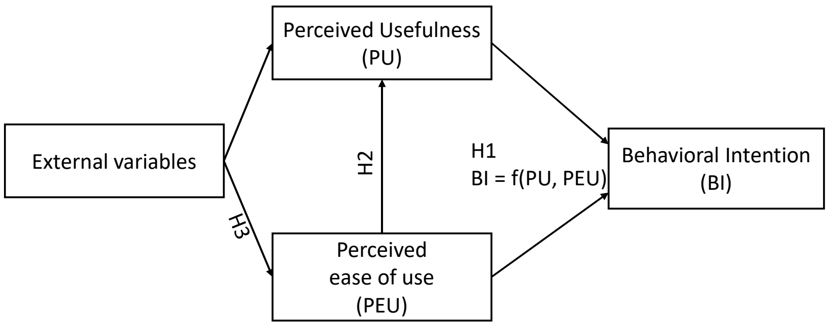

Figure 3.1.: Hypotheses to be tested within the TAM *(own illustration, adapted from F. D. Davis, Bagozzi, and Warshaw (1989))*

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4. Experimental Set–up

This chapter presents the experimental set–up followed in this dissertation, including the context for the experiments' organization and data collection, the applied data handling guidelines based on the findings from the previous sections, but also the framework for the driving simulator and naturalistic driving experiments. It is important to note though that only part of the experiments described have been executed and organized exclusively for this dissertation; these are the car driving simulator experiments which are described in detail in Chapter 5[a]. Excerpts of this chapter are presented in Al Haddad, Alam, et al. (n.d.).

[a] The rest of the experiments are mentioned as they are organized based on frameworks defined in this dissertation, although executed outside the scope of this dissertation.

4.1. Context: the i–DREAMS project

4.1.1. Objectives

The i–DREAMS project is an H2020 EU–funded project, which is the backbone of the experiments' organization and data collection described in this dissertation. The overall objective of project is to setup a framework for the definition, development, testing and validation of a context-aware safety envelope for driving ('Safety Tolerance Zone'), within a smart Driver, Vehicle & Environment Assessment and Monitoring System (i-DREAMS) (Fran Pilkington-Cheney et al., 2020). The Safety Tolerance Zone (STZ) has three phases: the normal driving phase where the crash risk is minimal; the danger phase where the crash risk increases due to the occurrence of external or within vehicle events; and the avoidable crash phase, where a crash would occur if no mitigating action is taken by the driver or another road user. Taking into account driver background factors and real-time risk indicators associated with the driving performance, as well as the driver state and driving task complexity indicators, a continuous real-time assessment is made to monitor and determine if a driver is within acceptable boundaries of safe operation. Moreover, safety-oriented interventions are developed to inform or warn the driver real-time, in an effective way as well as on an aggregated level after driving, through an app- and web-based gamified coaching platform. Figure 4.1 summarizes the conceptual framework for the project, which comprises the monitoring phase, the collection of diverse data (context, operator, vehicle), based on which task complexity and coping capacity are calculated, leading to an assignment of the situation to the correct STZ, according to which the appropriate interventions are implemented.

The key output of the project would be an integrated set of monitoring and communication

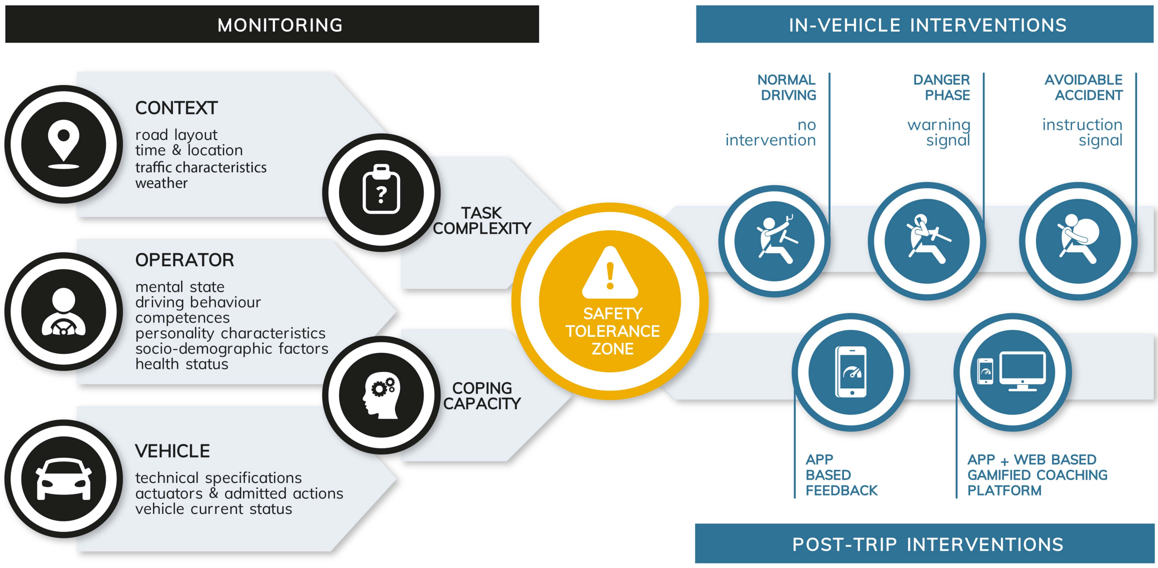


Figure 4.1.: Conceptual framework of the i-DREAMS platform (*source: the i–DREAMS consortium*)

tools for intervention and support, including in-vehicle assistance and feedback and notification tools, as well as a gamified platform for self-determined goal setting, working with incentive schemes, training and community building tools. The different stages of the project are summarized in Figure 4.2.

4.1.2. Devices and data collected

Various devices based on different technologies were used within the above–described experiments, resulting in different sets of data. Overall, the technologies were first tested in the driving simulator, to validate different driving behavior models, but also have first insights on drivers' acceptance of the system. Several simulators were used for the simulator trials including: car simulators in Germany and Greece, large vehicle simulators in Belgium and Portugal for trucks and buses, and rail simulators in the UK. The exact specifications of these simulator trials are presented in Graham Hancox, Rachel Talbot, Fran Pilkington-Cheney, et al. (2020). In particular, for the car driving simulator experiment in Germany (detailed in Chapter 5 as the data collected during this dissertation), data collection instruments can be summarized as follows:

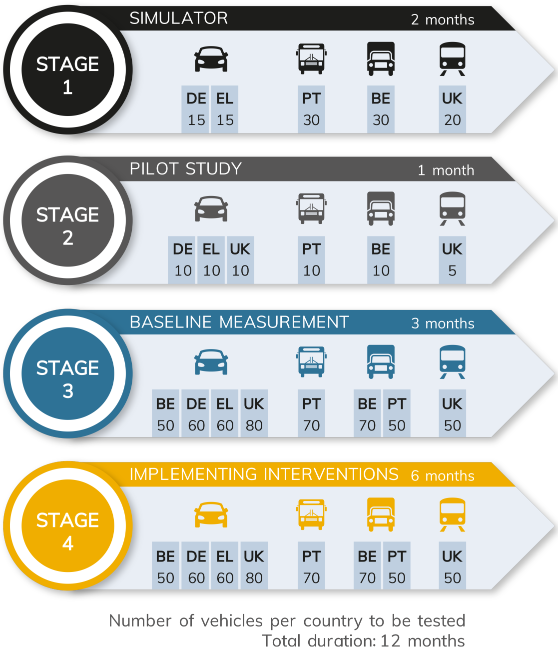


Figure 4.2.: A 5–Country 4–Stage experiment (*source: the i–DREAMS consortium*)

- Fixed–based driving simulator based on a Peugeot 206, including a dashboard, adjustable driver seat, steering wheel, accelerator, brake, and a warning–intervention system (referred to as the "i–DREAMS system") among other components (https://www.drivesimsolutions.com/) and operates on STISIM Drive 3. Three 49" 4K monitors with a 135° field of view are used to simulate the driving environment.

- Mobileye (https://www.mobileye.com/), a context–aware road monitoring system, used to trigger real-time warnings and measure driving performance parameters. In the experiments described in the remainder of this thesis, triggered warnings are forward–collision warning and headway monitoring, pedestrian collision warning, and distraction warning. An overview of the warnings and their descriptions is provided in Section 4.1.3.

- A wristband– PulseOn wearable (https://pulseon.com/)– to monitor heart rate and other related variables.

- Eye tracking glasses [1]– Tobii Pro Glasses 2 (https://www.tobiipro.com/) – to collect

[1]This was only used in the driving simulator experiments in Germany.

eye movement data (useful for assessing distraction). More information on visual tracking theory and Tobii Pro is given in Appendix A.4.

- Questionnaires: before and after the experiments, to capture participants' perceptions of driving and ADAS at different stages. An overview on the different questionnaires is given in Appendix C.2.
  - Recruitment questionnaire: includes age, gender, driving license duration (or year it was obtained), eyesight information (need for glasses while driving, and eye surgery history) as it was an important criterion for the use of the eye tracking glasses.
  - Entry questionnaire: includes questions on ADAS availability, ADAS frequency of use, attitude towards ADAS use, statements on distraction engagement. Most attitudinal questions were in the form of a 5–point Likert–scale agreement statements, ranging from "strongly disagree" to "strongly agree". Moreover, this part had questions on history of accident involvement, and fines for traffic offenses.
  - Exit questionnaire A: this was filled after completing the first two drives and included questions on the i-DREAMS system (also five-point Likert scale questions), mostly based on the study by M. M. Rahman, Strawderman, et al. (2018). Moreover, questions on the system included an assessment of the system's clarity, such as overall clarity, visual clarity, and sound clarity. Open-ended fields were also provided for participants to further elaborate on their feedback, and on what they believed could be improved.
  - Exit questionnaire B: this was filled at the very end of the experiments, and included additional open–ended questions about the system's strengths, and suggestions for improving it.

For the road experiments, the same technologies are used, with following differences:

- CardioWheel, an embedded system within the steering wheel is used to collect heart rate data, and the resulting extracted data. CardioWheel is to be used instead of the wristband for bus, trucks, and rail modes; for instance, ECG values and measures that are derived from the raw ECG signal, for example, drowsiness scale (KSS scale) are collected.

- Vehicle data (vehicle dynamics, GPS data, etc.) is collected and fused through a central communication component: the Gateway[2].

- Video data is collected through a dashcam, configured to collect data when specific thresholds of abnormal driving are met.

[2]While the Gateway also plays a major role in the driving simulator experiment, fusing the simulator data with the Mobileye data, for the on-road experiments, its role is even more crucial, as it ensures the entire communication, data collection and upload.

- App and platform data, providing scores for the driving performance, but also gamifications at different stages.
- Questionnaires for the on-road trials are quite similar to the simulator ones; yet, of course, there are some minor differences between the questionnaires.

4.1.3. Warning systems

The detailed warning list with their specifications is provided in Graham Hancox, Rachel Talbot, Brown, et al. (2021). Warning monitoring systems are summarized in Figure 4.3.

- Forward collision warning and headway monitoring.
  - Stage 0: Vehicle detected ahead.
  - Stage 0: Vehicle ahead is too close; time headway is displayed in seconds and only displayed when lower or equal to 2.5 sec and at speeds above 20 km/h.
  - Stage 1: Vehicle ahead is too close; time headway is displayed in seconds (1.3) and only shown at speeds above 20 km/h. Warning symbols accompanied by auditory signal.
  - Stage 2: Vehicle ahead is too close; time headway is displayed in seconds (0.6) and only shown at speeds above 20 km/h. Flashing icon, accompanied by auditory signal.
  - Forward collision warning: Avoidable accident ahead. Flashing icon, accompanied by auditory signal.
- Pedestrian collision warning.
  - Stage 1: Pedestrian detected in danger zone.
  - Stage 2: Avoidable accident with danger being imminent.Flashing icon, accompanied by auditory signal.
- Lane departure warning.
  - Stage 0: lane monitoring unavailable; occurs when no road marking is detected or when the vehicle speed is below 65 km/hr.
  - Stage 0: lane monitoring active and lanes detected.
  - Stage 1: lane departure warning. A dotted line appears on the side where the vehicle is leaving the road without using the indicator. Warning symbol accompanied by auditory signal.
- Distraction warning (based on phone use).
- Speed limit indication and over–speeding warning.
  - Stage 0: speed limit is detected (by the camera). Displayed in large for 1 second, then shown as a small icon on the home screen. The transition from Stage 0 to Stage 1 is variable and depends on the driver conditions.

  - Stage 1: vehicle speed is above the detected speed limit. Displayed in large for 1 second, then shown as a small icon on the home screen. The transition from Stage 1 to Stage 2 is variable and depends on the driver conditions.
  - Stage 2: vehicle speed is dangerously above the speed limit; speed must be reduced immediately. Displayed as a flashing icon in large for 1.5 seconds, accompanied by an auditory signal, then shown as a small icon on the home screen.

- Illegal overtaking warning.
  - Stage 0: No overtaking sign has been detected. Displayed large for 1 second, then shown as a small icon.
  - Stage 1: An overtaking maneuver in a no–overtaking zone has been detected. Displayed in large for 1 second.
  - Stage 2: An overtaking maneuver in a no–overtaking zone has been detected, combined with harsh acceleration. Displayed as a flashing icon for 1.5 seconds.

- Fatigue warning.
  - Stage 1: First signs of fatigue or sleepiness are detected. Displayed in large for 1 sec, then shown as small icon on home screen.
  - Stage 2: Elevated levels of fatigue or sleepiness are detected. Displayed in large and flashing for 1.5 sec, then shown as small icon on home screen. Warning symbol accompanied by auditory signal.
  - Stage 3: Dangerously high levels of fatigue or sleepiness are detected. Displayed in large and flashing for 1.5 sec, then shown as small flashing icon on home screen. Warning symbol accompanied by auditory signal. If the driver continues, the symbol is displayed in large again.

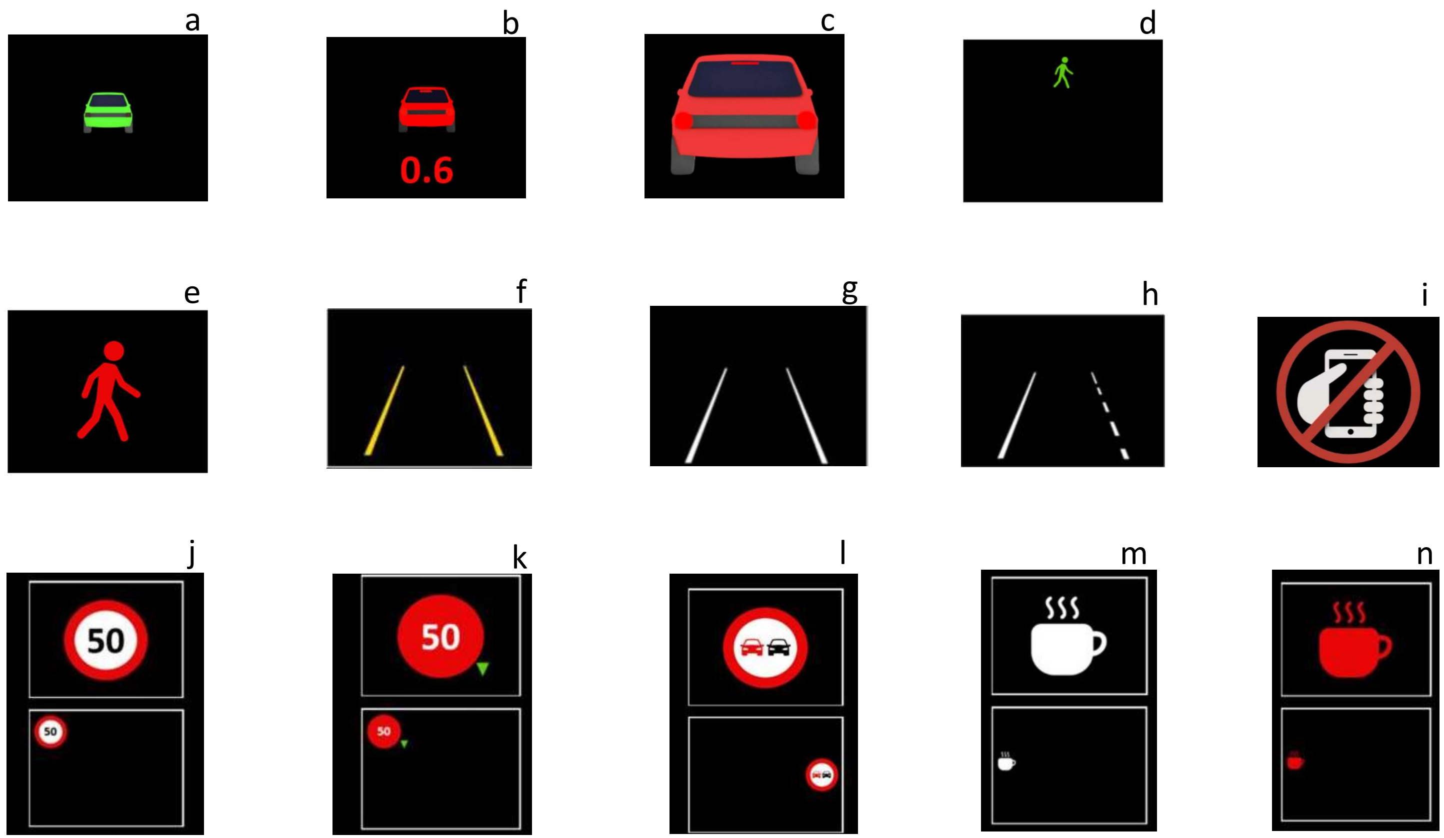


Figure 4.3.: Warnings symbols: a- Headway monitoring (normal driving); b- Headway monitoring (Stage 2); c- Forward collision warning d- Pedestrian warning (Stage 1); e- Pedestrian warning (Stage 2); f- Lane monitoring (Stage 0-unavailable) ; g- Lane monitoring (Stage 0 -active); j- Lane departure warning (Stage 1); i- Distraction (smartphone usage) warning; j- Speed limit indication (Stage 0- speed limit is detected); k- Speed limit warning (Stages 1 and 2); l- Illegal overtaking warning; m- Fatigue warning (Stage 1); n- Fatigue warning (Stages 2 and 3)–(*own illustration, based on the i–DREAMS consortium strategies*)

4.2. Data handling

The experimental set–up for the above–described project leads to an inevitable large amount of data collected. In this case, various partners play different roles in the data collection and processing pipeline. Project partners can be classified as follows:

1. Technology providers: these are CardioID[3], OSeven[4], and DriveSimSolutions (DSS)[5]. They provide the data collection equipment for the different countries and modes that are part of this NDS. Particularly, CardioID provide the sensory equipment, OSeven develops the android app, DSS builds the simulator and codes the scenarios for various trial partners. These partners (technology providers) must therefore ensure proper and consistent data collection and make it accessible to the rest of the partners. For field trials, this happens automatically through from the technology providers to their servers. For the simulator trials, the data collected is logged and stored locally in the simulator PC.

2. Trial partners: they are the simulator and field trial partners, and are responsible for organizing the experiments at their premises including collecting the questionnaire data, running the experiments, and managing the logistical aspects at their own premises. The different experiments (both simulator and field or on-road experiments) cover the different countries (Belgium, Germany, Greece, Portugal, the UK) and modes (cars, buses, trucks, and rail), as indicated in Figure 4.2.

3. Data processors: they are partners who contribute to the data analysis and processing. They have access to the data and test various hypotheses derived from the research questions.

Pilot data collected within this NDS provides a meaningful base to conduct analysis to test and investigate the performance of the developed system and then improve it prior to conducting on-road trials. Accordingly, a set of protocols for the adequate handling of this data is necessary, mostly as it involves multiple stakeholders (listed above). Based on the summary and lessons learned from Section 2.2.5, standard protocols for handling the data collected have been drafted for this dissertation, and are organized according to protocols for data collection, data preparation, data storage, and for legal and ethical considerations. These protocols are partially available in Al Haddad, Alam, et al. (n.d.).

4.2.1. Protocols for data collection

For country-specific trials, local partners from each country are responsible for the logistics of setting up the scenarios, leading to the collected data. However, data acquisition should be done through the same mechanisms (servers, communication protocol, code etc. should be similar, if not the same) to ensure consistency of processes and quality of data, even

[3] https://www.cardio-id.com/
[4] https://www.oseven.io/
[5] https://www.drivesimsolutions.com/

for country-specific scenarios. This is ensured by having common technology providers, who deliver the hardware equipment for the in-vehicle data collection. The frequency of collection should be decided a priori, given the fact that each sensor has a different frequency rate, and each sample has an associated timestamp for appropriate synchronization. Each data-collecting system should be conceptually tied to a vehicle, not a specific driver. Data is acquired within a trip session, which is defined from the moment the vehicle is turned on until it is turned off, with a grace period of five minutes.

4.2.2. Protocols for data preparation

Data pre-processing should be primarily done locally at the gateway and in the tech partners' databases. The pre-processing may include:

- Handling missing data (sensor and communication failure): with sensor failure, a trigger and alarm can be sent to the driver to ensure that nothing was disconnected (equipment in-vehicle). For real-time interventions for which input data is missing, data can be interpolated using the last known value or default value. For communication failure however, data is logged, so so that offline synchronization is possible even without any real-time communication. However, missing data can occur by the non-collaboration of the driver; it is therefore advisable to stay engaged and have good communication protocols with the drivers (participants).
- Ensuring temporal order in case of time-series data.
- Handling the time zone information carefully.
- Rectifying incorrect GPS data caused by reporting incorrect latitudes and longitudes when there are momentary losses of GPS signals. A filtering procedure may be implemented to remove these positional jumps. Moreover, raw GPS signals could be better managed when cleaned and simplified, using for instance the Ramen-Douglas-Peucker algorithm (Muckell et al., 2010). Since certain events (near-collision warnings) need to be mapped to an exact location, the two nearest-GPS points could be added per event to the simplified trace. This also would address the issue of protecting drivers' privacy in terms of their GPS locations.
- Pre-processing video data in a way to reduce data volume without compromising the quality of the videos. Metadata of the videos (event, timestamps, trip info etc.) should also be attached with each video for ease of future analysis. Video data pre-processing can help obfuscating sensitive information from videos (e.g., faces and number plates of surrounding vehicles).
- Detecting outliers and anomalies to ensure quality of data. Detection processes should be done at the source of collection when possible.
- Verifying data to minimize errors during the communication process. Such verification may include validation at the end of a trip session, ensuring temporal order of the data points, and verifying that repeating sample points are filtered out.

- Minimizing data loss at the retrieval/upload and verifying that data is consistent before deleting them from the vehicle. In case inconsistencies are identified, the vehicle data logger should be checked as soon as possible so that any issues can be recognized and fixed.

- Deleting vehicle data after the data have been backed-up and verified.

- Providing a description of the data variables (either from driving simulators, instrumented vehicles, or from questionnaires) by the technical partners generating the data. Having an understandable data format ensures consistency, completeness, integrity, and timeliness. Although survey data is static, a good practice would be for the related information to be attached to each instance:
  - Date and time (hh:mm) of start
  - Date and time (hh:mm) of end
  - Unique identifier: the link between this identifier and the personal data (name, address, etc.) is only stored at the local partners' premises, so that only them could cross-reference the data with the participant profiles.
  - If applicable, reference to file names and location.

4.2.3. Protocols for data storage

Partners have the freedom of choosing their preferred storage engines (databases, file systems) for local storage facilities. Nevertheless, the data should be automatically stored locally, via automatic transmission (WIFI, wireless, Bluetooth). Data can be stored in two types: onboard and remote storage (offline and online). Offline refers to storage systems which are not accessible through standard API to external world (other partners and/or third parties). Online storages refer to storage systems which are accessible through standard API to the external world (other partners and/or third parties). This may also include third-party cloud storage. Before being uploaded to the cloud, data needs to be pseudonymized. Data storage type is relevant in terms of data bandwidth (e.g., in the vehicle, the data is sampled from sensors at a very high rate, but usually only a portion of it is uploaded for analysis, or videos are continuously recorded but only a buffer is kept and stored whenever an event takes place, etc.), but also in terms of "sensitive" data; e.g., ECG data is processed locally in the vehicle to compute the Karolinska sleepiness scale score (Shahid et al., 2011).

The ECG data is not uploaded to the cloud server as it is too sensitive; only the derived indicators such as KSS score or heart pulse are uploaded. Once the data is uploaded, it is deleted from the vehicle to avoid misuse. To ensure proper handling of the data in offline storages, following requirements should be met:

- Persistence: data should be stored for at least till the end of the experiments.

- Reliability: periodic backups should be taken carefully. Deletion/modification of operations should be handled properly (consistency and validity).

- Availability: data shall be sent to the online data storage by uploading through the available API of the online storage system. Once available in the storage, data should be immediately available to the authorized user, preferably via an application programming interface (API).
- Serviceability: data may not be available up to a certain period during storage server maintenance (server downtime).

After transmission, data is downloaded (from the servers of the data collection equipment providers), and then saved to an online back-end server, which saves different components of the integrated and processed data.

4.2.4. Protocols for legal and ethical considerations

Prior to the start of the experiments, trial partners should have received an approval from their respective ethical committees, established contact with their respective DPOs, and have signed (preferably) a joint data agreement for the processing and use of personal data. This agreement, which remains confidential among consortium partners, distinguishes between data processors, data controllers, categories of personal data, and specifies how data leakage or breaches of the agreements are to be reported. Different granted permissions would give different roles for access to different people. This agreement can be useful in providing the details of use of personal data among consortium partners until the end of the project and even after it.

Experiments and data collection can only take place after participants have signed an informed consent, where they give partners permission to collect and process their data during the experiments. Their personal information may then be collected, after which a unique identifier is assigned to the participants, which is a cross-reference between the experiment data and their personal data. The personal data should be encrypted to ensure security, and placed in an offline file system, only accessible to limited people (to be defined, typically the DPO and persons of contact assigned for the experiments). Only the local partner has the access to the unique identifier which can point to a participants' personal data.

Each partner is therefore responsible for the proper pseudonymization of their participants' personal data. When collecting data from professional drivers (trucks, buses), and when working with professional companies, i.e., employers of the participants, an agreement is also necessary between the field trial partner and the company, stipulating how confidential information is exchanged within the project framework between the company and the field trial partner.

Servers and hard drive encryption (following GDPR recommendation, article 34, recital 83) should ensure that all data (including non-personal) is protected (including local storage in the vehicle), as a mitigation against breaches, even if the data is pseudonymized. In case of sharing among partners residing in different countries and to assure compliance with privacy regulations, the local partner needs to clear the simulation hardware of collected data before handing over the hardware to another partner. This is for instance the case for simulator experiments conducted in Portugal and Belgium, which share the same large vehicle simulator.

Following the agreed time after the end of the project (typically five years), the following procedures can be applied for anonymization and for making the data accessible in an open-source platform according to the project objectives: (1) The unique identifier that connects the data in the partners' databases with the personal data of the user is replaced with a random number. The process would then be irreversible and there would no longer be any possibility of relating the data in any database with the personal data of the user; (2) In case the primary data (including location data) relates to the driver ID, the latter is then replaced by a random code for each trip. This process is irreversible and there is (i) no longer any possibility of linking the primary data of the trips (including location data) to the personal data of the driver and (ii) no longer any correlation between the trips of a user. Following the above procedures, the data of the driver would be fully anonymized since it would then be impossible to trace collected data with a natural person.

The extent to which these exact procedures would be applied would depend on the approval of the respective DPOs and would need to be agreed between consortium partners. To transfer data efficiently, each partner generating data should either provide API access on their own data or upload the data to a back-office server from where other partners can collect the data. If an API is exposed to transfer data from the responsible partner's side, an API specification is also expected from the partner. These APIs should also be secured through an authentication mechanism. Similarly, the back-office data should also provide an API specification listing out how to access data which are available through its API; specifications remain confidential among consortium partners.

To access the data, different user types should be first defined with different rights of access (e.g., superadmin, admin, user etc.). A list of roles shall be made, with a distinction between data access during the project lifetime, and after the project end. No deletion/modification permission would be given to any user of the storage; only reading permission would be provided to the appropriate users. Exceptions can take place in extraordinary circumstances and are contingent upon approval of the superadmin (consistency and validity). Data access should follow safe protocols with access points encryption.

Transferring data should take place over HTTPS and hence would be secured with public/private key encryption mechanism. Access to the data should follow joint agreements set out between partners and access to the data should be logged to trace back any problems of data leaks. Pseudonymized data shall be accessible to consortium partners, according to joint data agreements. Personal data shall be only accessibly locally by authorized personnel and shall not be stored longer than necessary. A duration of five years (in the case of the i–DREAMS project) has been advised as suitable by relevant DPOs and should be agreed by respective parties (for the personal data). An anonymized portion of the data (a few datasets) can be made available and offered to third-parties at the end of the project. According to the GDPR, however, these data should exclude personal (and sensitive) information.

In Germany, the organization and collection of data within the driving simulator and on–road experiments have been reviewed by the university ethical committee ("Ethikkomission der Technischen Universität München"), and approved, following a few rounds of amendments. In particular, the driving simulator study has been first approved (reference number 78/20 S-KH), followed by an approval of the road experiments (reference Number: 748/20 S-KH). The above ethical review applications have been submitted, reviewed, and granted, as part of the work done in this dissertation.

4.2.5. Protocols implementation

Based on the above-drafted protocols, a set of guidelines were implemented within the scope of the presented case study, which are summarized as follows in Table 4.1.

Table 4.1.: Implementation of previous findings in i-DREAMS (*source: own*)

Previous findings	**i-DREAMS**	**Remarks**
Reliability and validity checks	✓	No delete/modify permissions are given to any users of the storage.
Common DAS	✓	
Minimize number of vehicle models	✓	Choosing the vehicles most compatible with the data collection devices.
Centralize responsibilities for coding, processing, and analysis	✓	
Data pre-processing prior to storage	✓	Done at the gateway and the tech partners' databases.
Advanced video processing techniques	✓	Done to obfuscate sensitive data.
Data sources	✓	Using weather data, roadway geometry, and maps, where possible.
Ease of access of data	✓	Central back-end API.
Systematic back-ups	✓	
Data well defined and understandable	✓	Data management plan.
Video files stored separately, but linked with the rest of the data in file management systems		Should be possible in i-DREAMS.
Transferring the data should be done automatically	✓	Except for the simulator data (stored locally in the simulator PC.
Store hard copies for manually extracted files like questionnaires and forms	✓	Paper-based questionnaires (consent forms) will be backed-up and hard copies will be adequately stored.
Ease of access of data	✓	Using the recommended architectures.
Consent of participants	✓	
Data agreements	✓	
Following GDPR	✓	
Data pseudonymization	✓	
First and last minutes of driving deleted	✓	
Driving across multiple countries	✓	Based on geofencing, the dashcam will be disabled from recording in countries where its use is not allowed
Non-participant driving the vehicles incidentally	✓	Driver identification at the beginning of each trip. If participant not identified, recording stopped
Data use after project lifetime	✓	Defined within national ethical and DPO committees, for the use by local partners

4.3. Driving simulator experiments

4.3.1. Experimental design

The detailed experimental design and checklists for the driving simulator experiments across the different countries are given in Fran Pilkington-Cheney et al. (2020) and Graham Hancox, Rachel Talbot, Brown, et al. (2021). Where possible, the driving simulator experiments follow the recommendations and guidelines defined in Section 3.1.1, based mostly on the design guidelines defined by Fisher et al. (2011).

The outcomes, predictor and hypotheses were defined according to the main objectives of driving simulator trials in this project and the corresponding research questions developed for these trials. The primary outcomes were defined as the real-time interventions, while predictors were defined as risk factors including fatigue, sleepiness, speeding, forward collision avoidance, lane discipline, overtaking, vulnerable road user collision, number of harsh accelerations/ decelerations and steering. The hypotheses were drafted on the risk factors, and the impact of the interventions and conditions (example distraction) on the defined critical events.

Further, the sample size for the simulator trials was pre-defined based on limitations and resources, and mainly because the primary objective of the simulator trials is to test the technology and real-time interventions (in a set of pre-defined risk factors). As a result, the statistical power of the trials is also affected by this. Still, for each mode, a minimum of 30 participants has been defined. The experimental design is a fractional factorial design, where only a subset of all scenarios is selected. This is due to the large number of risk factors resulting in an abundance of combinations for experimental trials in a full factorial design. The statistical significance level is (in most cases) set at 0.05 (5%).

Further, the experiments are designed on a within-participant basis because the sample size is limited (30 participants per transport mode[6]). Since triggering real-time warnings by the i-DREAMS technology is achieved from the same gateway for all risk scenarios, multiple risk events can be included in the same scenario, which increases within-participant variability and consequently the statistical power of the overall project study. In addition, including multiple risk events in one scenario is more efficient and reduces the overall number of scenarios and trials. However, this approach presents some limitations for fatigue testing, as experiencing risk events with greater frequency than would be expected in normal driving may have alerting effects.

The order of scenarios and events was randomized among the participants and during the trials. Due to the small sample size and the high number of risk events, the duration of the simulator trials were initially defined based on the upper allowable limits (two hours in total, with each trial up to one hour and a 10-minute break in between), based on the recommendation from Fisher et al. (2011). Therefore, the maximum number of risk events can be included in each scenario while preventing simulator sickness. In addition, several practice drives were included prior to the intervention scenario to familiarize participants

[6]In Germany, for the purpose of this dissertation, an additional effort was made to increase this sample size to 60, as will be elaborated in Chapter 5.

with the simulator device and reduce simulator sickness.

To test the confounding effects and effect modification, an additional drive was included in the experimental design in which environmental conditions serve as a condition for driving behavior. While target risks for different transport modes (i.e., car, bus, truck) may vary, on-road vehicles share similarities.

For each mode, one to two risk factors were targeted. Each risk factor is captured by several separate events, to ensure adequate validity of the observations per risk factor. Moreover, several "neutral" events are used, creating a realistic driving scenario and minimizing confounding effects (e.g. order/learning effects). The scenarios were defined over three drives. One drive is a baseline scenario without interventions, the other has interventions with fixed–timing warnings, and another scenario includes variable–timing warnings. The intervention scenario with variable timing warnings would be for the scenario including a condition (e.g., fatigue/sleepiness, distraction or bad weather), used to adapt the timings of the warnings related to the primary risk factors, for example, the warning for forward collision avoidance would be given sooner in bad weather. However, it should be noted that fatigue may need separate consideration in the design. Past studies have shown that participants in driving simulators are usually fatigued after 20 to 90 minutes of monotonous driving (Philip et al., 2005; Desai et al., 2007; Saxby et al., 2007; Ting et al., 2008; Rossi, Gastaldi, and Gecchele, 2011; Chunlin Zhao et al., 2012; Merat and A. H. Jamson, 2013). In the i-DREAMS study, fatigue can be indicated by the number of hours driven, under the assumption that long and monotonous driving may induce fatigue directly, or indirectly through sleepiness; this however would mostly be applicable for on–road experiments, where participants drive for several hours, as opposed to limited driving duration within the driving simulator experiments.

4.3.2. Multi–modal driving simulator experiments

As previously indicated, the driving simulator experiments were conducted in various countries, to assess an array of risk factors in different modes[7]. A summary of these experiments is given in Table 4.2, and visualized in Figure 4.4.

[7]It is important to note that the summary below does not include the car experiments conducted in Greece (as mentioned in Figure 4.2), as these were not yet conducted until the time this thesis was written.

Table 4.2.: Characteristics of the multi–modal driving simulator experiments (*source: own*)

	Transport mode	Car	Tram	Truck	Bus
	Country	Germany	UK	Belgium	Portugal
Risk factors	Forward collision	•		•	•
	Illegal overtaking				•
	Over–speeding		•	•	
	VRU collision	•	•		•
	Distraction	•			•
	Fatigue/ sleepiness		•	•	
	Environment	Rural Urban Highway	Urban Suburban	Rural Highway	Rural Urban Highway

Figure 4.4.: Driving simulators for the different modes: a- Passenger car (DSS), b-Truck (DSS heavy vehicle simulator), c-Tram (Croydon tram simulator); *source: own illustration*

4.3.3. Car driving simulator experiments

As mentioned in Section 4.3.2, risk factors investigated in Germany[8] were tailgating and vulnerable road user collision. The number of risk factors was considered adequate for a 45-minute session and was split into three scenarios, one for each drive (each 15-minute), in addition to a baseline drive beforehand. In the third drive, the impact of distraction on the chosen risk factors and critical events was investigated. The design of these experiments followed the driving simulator guidelines set out in the project and presented in Section 4.3.1. The detailed scenario design for the car experiments in Germany is given in Amini et al. (2021).

In particular, for each of the tailgating and vulnerable road user risk factors, three critical events were designed, and randomized across three road environments: rural, urban, and

[8]These pertain to the data collected during this dissertation.

highway. To investigate tailgating, a lead vehicle was placed in front of the driver, to measure car following behavior (under safe driving conditions). For the VRU events, the pedestrians started crossing at a speed of 1.2 m/sec. The critical events (CEs) for each of the risk factors are summarized in Table A.3 of Appendix A. Moreover, to introduce randomization and to prevent learning and confounding effects in the dataset, the Latin square method (as implemented in Ryan et al. (2020)) was followed to change the order of the traffic environments associated with a particular drive scenario (intervention or distraction); the latter is described in detail in Table A.4 of Appendix A.

An overview of the risky events for the car driving simulator is given in Figure 4.5; here, (car)1 refers to the driver and (car)2 refers to the car driving in front of the driver within all risky events.

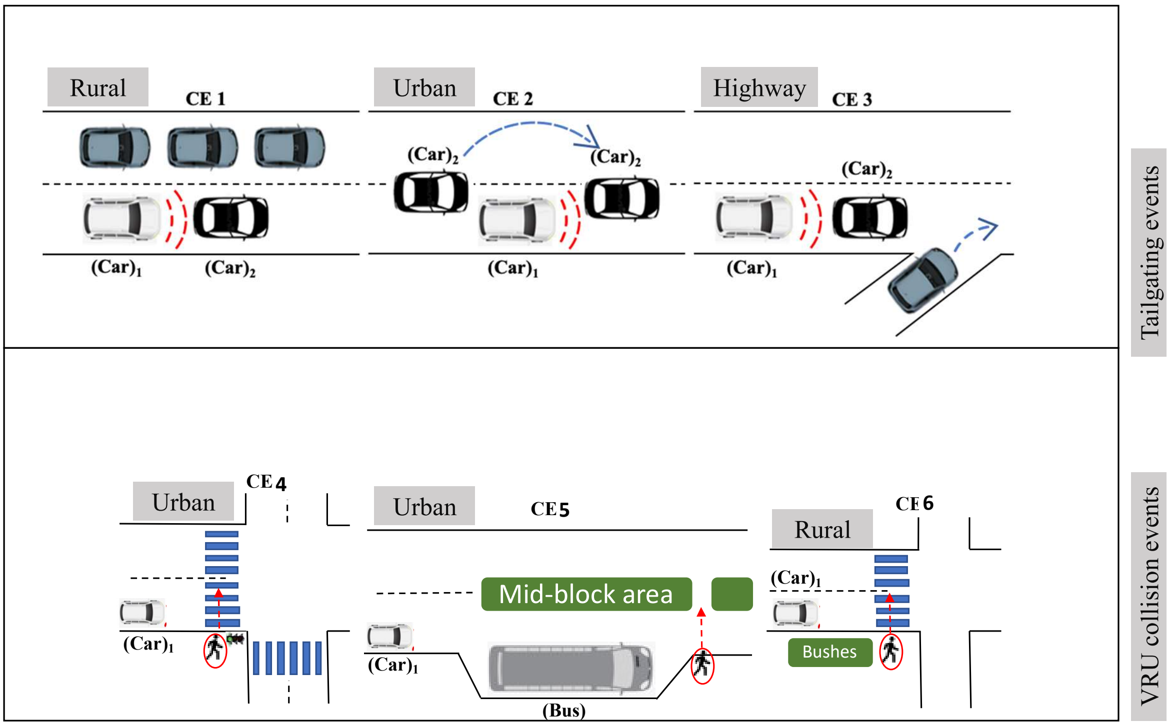


Figure 4.5.: Risk event sketches for the car driving simulator experiments; *source: own illustration, adapted from Amini et al. (2021)*

For the third drive, where distraction was investigated, participants were asked to drive as before, with the additional task of reading and responding to text messages using a smartphone. In total, six text messages were triggered before the critical events, and two when there was no event. In total, eight text messages at two levels of simple and complex were sent to participants during the third drive, in which: six text messages were triggered before the critical events, and two were triggered when there was no event. Before the trial, participants were trained to only reply to the text messages, which are in the form of a question. The text messages were sent or received both in German and English, depending on participants' preferences. A summary of the distraction types across critical events is given in Table A.5 of Appendix A.

Instruments used in this study have been described in Section 4.1.2; in particular, for the car driving experiments conducted in Germany, an overview of the equipment used is depicted in Figure 4.6.

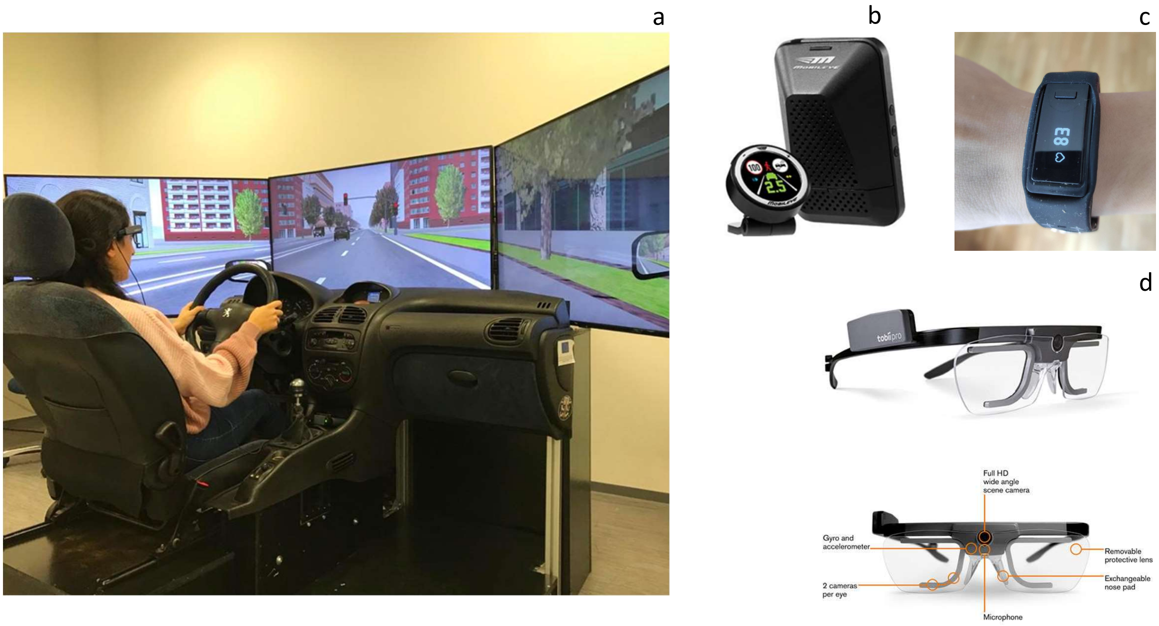


Figure 4.6.: Data collection instruments. a-Fixed driving simulator setting; b-Mobileye system; c-PulseOn wearable, d-Tobii Pro Glasses 2 (eye tracking glasses); *source: own illustration*

4.4. Naturalistic driving experiments

4.4.1. Field trial protocols

The aim of the field trials are to assess the effect of the interventions developed as part of the i-DREAMS system, for both real–time and post-trip warnings. As shown in Figure 4.2, the field trials are part of the large–scale 4–Country 5–Stage experiment to be conducted across Europe in five testing sites, covering different transportation modes. Following the learnings made in the simulator experiments, the aim of these naturalistic driving experiments is to test the developed technology[9], in which all drivers for different modes would be engaged for each of the baseline and intervention stages (Stages 3 and 4 of Figure 4.2). Prior to that,

[9]Participants for each of the simulator and on–road experiments are different, to prevent biases and not to influence the results.

a pilot stage (Stage 2) would ensure that the equipment and technology are working as planned. For the baseline stage, no interventions are implemented, in order to provide a basis for comparison when analyzing the impact of interventions on driving performance. In the intervention stage (Stage 4), both real–time and post–trip interventions or warnings are implemented; due to limited equipment and fitting capacity, participants are divided in two groups or waves, mostly for passenger cars. For the final stage, or the interventions stage, participants receive feedback through a smartphone application and/or a gamified web platform. The ultimate goal of the field trials would be to successfully capture the necessary indicators, performance metrics, and intervention characteristics, that can assist in validating the STZ for each mode, to select the most successful in-vehicle interventions.

To summarize, the third and fourth stages span across 18 weeks, and are organized over two groups of participants, as follows:

- Phase 1 (4 weeks): baseline measurements with no interventions activated
- Phase 2 (4 weeks): in–vehicle real-time interventions activated (auditory and visual)
- Phase 3 (4 weeks): post trip feedback (smartphone app)
- Phase 4 (6 weeks): post trip feedback (smartphone app) and gamifications

4.4.2. Practical aspects

Based on field trial recommendations provided in Chapter 3, the following plan for implementation was followed for road trial planning of the presented NDS. This includes an update of the FESTA checklists, tailored specifically to the case study, which can be summarized as follows:

1. Plan of approach: a set of checklists and forms was developed on a project-wide level, which was then adapted for each country and mode. The detailed lists are provided in Graham Hancox, Rachel Talbot, Brown, et al. (2021).
2. Participant recruitment: while attempting to meet the recruitment requirements, vehicles with multiple drivers were recruited to facilitate the process, if all drivers drove sufficiently (a set of minimum kilometers per week was defined); this procedure would also help saving on the number of installations (within a reasonable amount) and therefore the associated installation time and costs.
3. Participant incentives: participants were given incentives for their participation in the experiments; the amounts however differed for each country. In Germany, incentives were paid in the form of vouchers, worth 50 EUR for a pilot participation, and 250 EUR for a full participation (18 weeks), in order to mitigate legal university requirements, but also to avoid a long bureaucratic process that would allow participants to be paid money (either cash or by transfer).

4. Vehicle instrumentation: the equipment needed to be fitted by professional and trained technicians. For legal purposes, the dashcam and Mobileye were installed in a way that would not obstruct vision. For trucks and rail, CardioWheel needed was firmly installed, so as not to be moveable on the wheel (firmly attached) and to not have trailing wires blocking drivers' movements.

5. Participant handling: a set of frequently asked questions (FAQs) was given to participants, as most questions tended to be asked by various participants.

6. Ethical and legal considerations: a set of guidelines and documents were developed for the project, to cover different needs for the different modes. Although the project did not have any foreseeable legal barriers to technology fitment or use, project partners recommended the creation of a project fact sheet detailing equipment, who to contact etc., to be kept in the vehicle's glovebox. This would be referred to as "the user manual". This manual also included an explanation on the safe use of the installed equipment, especially when the vehicle is moving (i.e., systems would not replace drivers' responsibility to observe the road and react accordingly; the drivers should not rely too heavily on the system warnings, as the i-DREAMS technology is only "assistive"). Further, a project wide data policy was deemed necessary to develop guidelines on what to do if dangerous driving was witnessed on the videos (despite having no legal obligations to do share this video data, perhaps it was morally advisable to hand it over to authorities, depending on the frequency or severity). The same applied for a procedure concerning the request for footage by the police. Moreover, it was advised that different countries check their own insurances regulations; two aspects were important to consider: a public liability insurance (to cover damages claimed against the installation, or any claims participants might have with regards to the conducted experiments, in case of incidents or other events) and participants' existing insurances (to clarify whether installing the additional devices would invalidate any of the existing insurances participants might have).

   In Germany, rules were consulted with the university legal office regarding public liability insurance. A first consultation revealed that in case of liability claims, the university would be covered by the Free State of Bavaria. However, as the assessed risk could possibly be high in the event of a serious crash, permission for obtaining a liability insurance was granted, and a subscription to a liability insurance was made. Another effort on understanding vehicle insurances in Germany revealed that despite most insurances not providing any binding information, they seemed quite positive that vehicle insurances would not be affected by the installation of the i-DREAMS technology. In other words, the terms and conditions of the existing contracts would not change based on participation in the project; on the contrary if so, some insurances would offer discounts for in–vehicle ADAS installation. In Germany however, the use of the dashcam remained controversial. In essence, there was a lack of consensus or clear regulations on dashcam installations in Germany. Owning the dashcam and recording events per se seemed to be legal or at least not illegal; however, the exact terms and conditions for using such data was quite uncertain. According to GDPR (article 6), an impermissible permanent filming and storing of public road traffic footage remains prohibited. Accordingly, it was agreed that in Germany, dashcams would not be permanently switched on, but rather used only to record a specific situation (dangerous event). Recordings were to be stored only for a short time, to not endanger personal rights of participants and other road users who did not sign up for the experiments; to avoid storage, a loop function was recommended.

5. Data Collection and Analysis

This chapter presents the outcomes of the data collected in the scope of this dissertation (car driving simulator data in Germany), including the detailed protocols for the experiments planning and organization, based on the guidelines developed in Chapter 4. The following sub–sections provide an overview of the practical aspects for those experiments, but also first insights and visualizations of the outcomes obtained. Parts of the results presented are given in Al Haddad, Abouelela, Kris Brijs, et al. (n.d.).

5.1. Practical aspects of experiments

The study design for the German car experiments followed the study protocols elaborated in the previous sub–sections, in particular sub–sections 4.3.1 and 4.3.3. The methodology set out for these experiments can be summarized in Figure 5.1.

5.1.1. Planning and organization

Participant handling and experimental protocol

- Participant handling ensured that all necessary forms were filled by participants, in order to comply with the ethical, and data protection regulations that are necessary for this type of study. In particular, participants were first briefed about the experiment and what they were required to do (i.e., drive in the simulator and fill some forms), after which they filled a consent form (to take part of the study, which was voluntary) and a data protection form (for their consent to allow the processing of their data for research purposes).
- Entry questionnaire[1]: initial attitudinal questions about ADAS and driving perceptions.
- Practice drive, and drives one and two (monitoring and intervention, respectively): aimed to familiarize participants with the driving simulator itself. In this drive, the eye tracking glasses were calibrated to the participants. Then, the first two drives were completed. The first drive was a baseline drive, during which no warnings were triggered. The second drive was a drive with interventions, during which real–time warnings were triggered.
- Questionnaire Exit A: after completion of the first two drives, to assess participants' perceptions towards the warning system.

[1]Details on the content of the different questionnaires is given in Section 4.1.2.

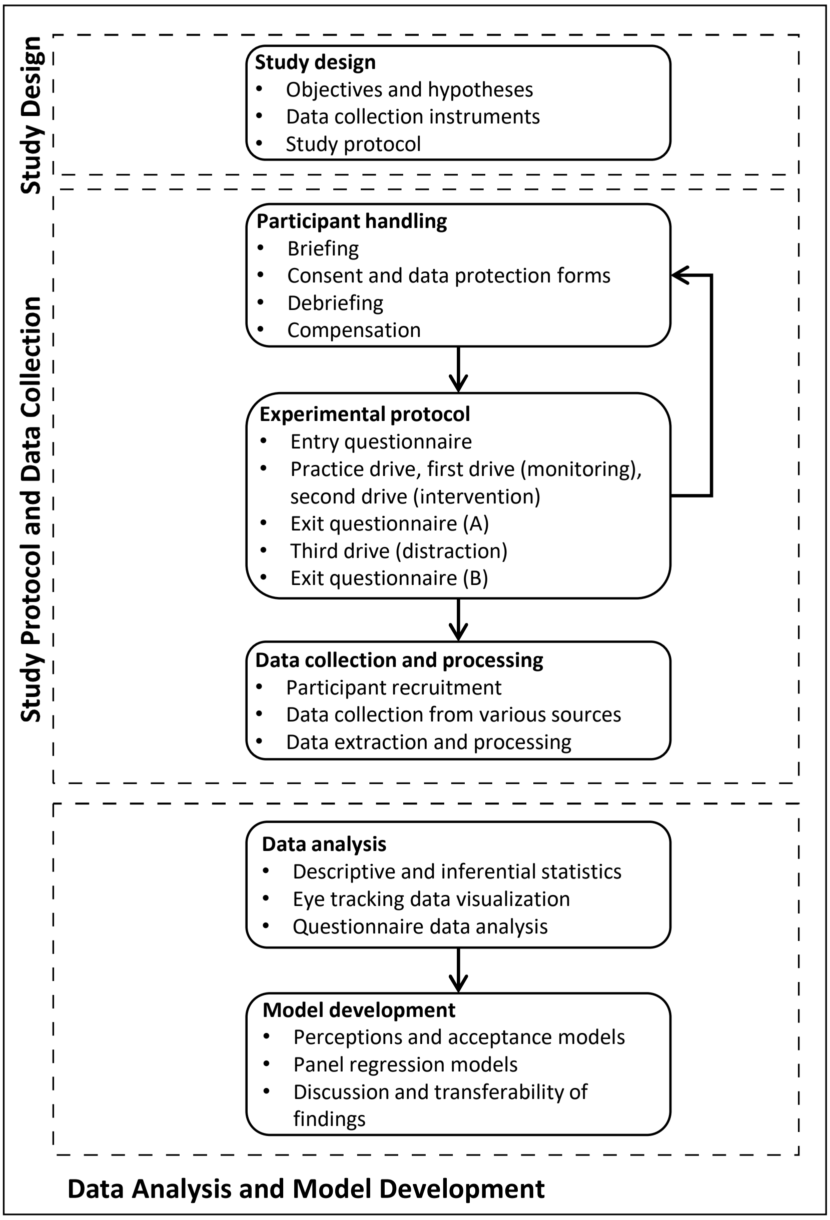


Figure 5.1.: Study methodology (*own illustration*)

- Drive three: distraction drive. In this drive, the same scenario as before was given (with different order of events); however this time, participants were requested to read and respond to text messages. For all three drives, participants wore eye tracking glasses. The aim was therefore to see how their eye movements changed between different drives, in different conditions (with and without distraction).

- Exit questionnaire B: final questionnaire, filled after the final drive, aiming at assessing one more time participants' perceptions towards the warnings and their effectiveness.
- Debriefing: after the end of the experiments, aiming at informing participants that texting while driving was only requested to assess the impact of distraction due to mobile phone use during driving; it was important to stress this out, to highlight that texting while driving was by no means encouraged. Debriefing was done however after the completion of the experiments, to not bias participants' behavior in the distraction scenario.
- Compensation: given to participants upon completion of the experiments, as an incentive, or rather thank you for their participation.

A comprehensive list of forms and questionnaires given to participants is presented in Appendix C, in Sections C.1 and C.2, respectively.

5.1.2. Data handling for the collected data

The car simulator experiments conducted in Germany followed the data handling requirements set in Section 4.2. In particular, the experimental set–up was reviewed by the university ethical committee. A first proposal was submitted to the university ethical committee ("Ethikkomission der Technischen Universität München") on the 17th of February 2020; following feedback and amendments, a revised application was submitted and finally approved on the 30th June 2020 (reference number 78/20 S-KH). Only after that, were recruitment and advertisement for the study possible. Moreover, since the data collected involved personal and possibly sensitive data, it was necessary to ensure compliance with data protection regulations; in particular, data handling needed to follow GDPR (European Commission, 2018). Accordingly, an application for the adequate data use and processing was made to the responsible (local) data protection entity at the university; the application was then reviewed and approved.

5.1.3. Challenges: the COVID–19 pandemic

At the time of data collection, COVID-19 was an ongoing pandemic. This had an impact on the project as a whole, but in particular on the contributions of this dissertation, namely data collection in Germany. This translated to delays in delivering the equipment and the driving simulator. Recruitment was therefore of course impacted, but also the planning and organization of experiments. For a significant period of time, access to the university was restricted to authorized personnel, to conduct only "essential" activities. Despite having contacted the "corona crisis" unit of the university, and even with a suitable authorization to carry on the data collection[2], it was still a grey area for a while at least, whether or not third–party (non–researchers) participants could access the university and participate in the experiments. This therefore led to the inevitable rescheduling of experiments, and the

[2] An approval from the unit was not obtained, but neither was an objection expressed.

consequent delay in the start of the study, until it was deemed more suitable for participants to access the simulator facility.

5.2. Data collection

5.2.1. Sample and demographics

Participants were recruited through various channels: online (social media, LinkedIn, websites, mailing lists, etc.), but also offline (posters with the necessary information). The inclusion and exclusion criteria followed the guidelines set out in Fran Pilkington-Cheney et al. (2020). The aim was to recruit a sample representative of Munich's driver demographics. However, since the latter was not easily obtainable, this was then changed to a sample representative of Munich's population. Inclusion criteria included having a valid driver's license, and being above 18 years old. Exclusion criteria included wearing glasses during the experiment (contact lenses were acceptable), or having had previous ophthalmic surgeries, as these points would not allow an adequate data collection using the selected eye trackers.

The recruitment resulted in over 100 interested participants, out of which 60 were selected and conducted the full set of experiments[3]. Table 5.1 presents the sample characteristics for the 60 participants, including gender, age, driver's license duration (the number of years since a participant has obtained his or her driver's license), and vision impairment (important when considering the eye trackers). The average and percentage values are provided for gender and vision impairment (as they are categorical values), whereas median and interquartile ranges are given for age and driver's license duration (as they are continuous values). Beyond these variables, the entry questionnaire reflected that most participants did not have medical problems (97% of participants), nor previous accident history (93%), or fines (only 31% of participants have had one or more fines in their lives–particularly 30% of those were over–speeding fines).

Table 5.1.: Socio–demographics characteristics of sample data (N=60)

Variable		Statistics
Gender	Male	25 (42%)
	Female	35 (58%)
Age		30 (26, 37)
Driver's license duration (years)		9 (6, 15)
Vision impairment	None	43 (72%)
	Yes (contact lenses)	14 (23%)
	Yes (no glasses, no contact lenses)	3 (5%)

[3]To reach this number, actually 62 participants participated in the experiments, out of which two could not complete the runs due to simulator sickness.

5.2.2. Data types

Data collected within i–DREAMS is highly heterogeneous and results from a variety of sources and instruments, as elaborated in Section 4.1.2. In particular, data collected in the simulator experiments in Germany[4] is detailed in Section 4.3.3, with a schematic representation of the instruments in Figure 4.6. This data comes from different sources, namely:

- Simulation data including the driving simulator dataset (details on the simulator parameters are provided in Appendix A.2.), the Mobileye dataset, the bracelet biometric dataset[5].
- The eye tracking dataset (exported from the eye tracking device).
- The questionnaire datasets (including the different demographics, and attitude questionnaires; an exhaustive list of questionnaires is provided in Appendix C.2).

5.3. Data processing

Data collected within the car simulator experiments in Germany resulted in a multitude of datasets, of different types, as mentioned in Section 5.2.2. A necessary step is therefore the processing of data in order to extract the needed variables for analysis. This section presents the detailed data extraction of variables resulting from the driving simulator (Section 5.3.1), and from the eye tracking glasses (Section 5.3.2), and a summary of selected variables (Section 5.3.3).

5.3.1. Driving simulator data extraction

The simulator software automatically collects driving parameters at frame rate (+/-60 Hz). Further, for the purpose of the described experiments, the files generated by the simulation also integrated external data including the ones from Mobileye, and the biometric data generated from the bracelet; this data was then automatically collected and saved. A full list of the driving simulator parameters and specifications are provided in Appendix A.2. For the purpose of analysis, this data was then extracted and aggregated per event, and then used to compare driving performance between different driving conditions and safety–critical events.

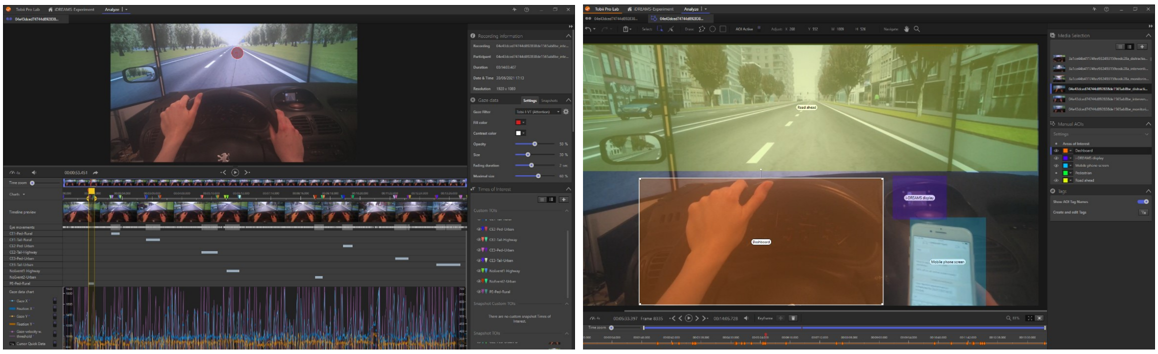
5.3.2. Eye tracking data extraction

To extract relevant eye tracking metrics, recordings containing participants' eye movement data and associated information like drive scenario (monitoring, intervention or distraction) were imported into the Analyzer module of Tobii Pro Lab V1.162 (AB, 2014). Each recording was analyzed individually after adjusting for time offsets (approximately 1s) to synchronize

[4]Data collected in the scope of this dissertation.

[5]The biometric dataset will not be used in this dissertation, but would be more relevant for assessing risk factors such as fatigue for professional drivers, where longer driving hours are collected.

the starting times of both the simulator and eye tracking recordings. Selected eye tracking metrics were exported for the defined times of interests (TOIs) and areas of interests (AOIs). TOIs, were the defined intervals of interest, for which the analysis was focused and extracted; in our case the starting and ending points of critical events, which were manually defined. AOIs were the areas defined, to assist the extraction of glance behavior on a particular area, including the extraction of metrics such as fixation count and total fixation. For the distraction scenario, five AOIs were created: the road ahead, the dashboard, the i-DREAMS display, the mobile phone screen, and the pedestrian area. The first three were kept active all the time, while the mobile phone screen was activated only when the use of the phone was relevant, i.e., when drivers were requested to read or respond to a text message using the mobile phone. Similarly, the pedestrian AOI was only activated during critical events involving VRUs. For the remaining recordings (baseline and intervention recordings), all AOIs were used, except the mobile phone screen, as no texting or mobile phone use was part of those drives. As both driver movements and the simulation scene were highly dynamic, the AOIs position and sizes needed to be constantly (manually) adjusted. The required metrics from the analyzed recordings containing information about a particular AOI during a certain TOI were then exported as CSV files. An example of the Analyzer module interface, including both AOIs and TOIs is given in Figure 5.2.



(a) The Time of Interest (TOI) interface

(b) The Area of Interest (AOI) interface

Figure 5.2.: Interfaces in the Analyzer module of Tobii Pro Lab V1.162 (*source: own illustration*)

While various metrics could be of interest for visual tracking analysis (as mentioned in Section 1.2.2 of the introduction), the ones selected for the purpose of this research are the the total fixation duration and total fixation count for the areas of interest. Fixation Count (FC) is the total number of fixations present on a particular AOI (Sharafi, Soh, and Guéhéneuc, 2015; Tobii Pro AB, 2020). Goldberg and Kotval (1999) noted that a higher number of fixations on a specific AOI due to an induced stimulus meant that the subject was not able to cognitively gather relevant information he or she was looking for efficiently. Previous eye tracking studies used this variable to single out AOIs that attracted more visual attention/gaze. A higher value for this metric was also used to imply that more visual effort was required to perform a specified task. Total Fixation Duration (TFD) has been defined as the sum of the durations of all fixations on an AOI during a specified task (T. Busjahn, Schulte, and A. Busjahn, 2011;

T. Busjahn, Bednarik, and Schulte, 2014). This metric can also be obtained as the summation of all dwell times by a subject on a particular AOI during the entire duration of a task (T. Busjahn, Bednarik, and Schulte, 2014). The purpose would be to eventually assess based on these metrics the attention drivers had on one area as compared to another.

5.3.3. Summary of data collected and processed

A summary of the variables selected for analysis, including the simulator and eye tracking variables is given in Table 5.2.

Table 5.2.: Selected simulator and eye tracking variables

Category	Variable	Explanation	Unit	Remark(s)
Longitudinal control	Long. vel. (mean, max.)	Longitudinal velocity	m/s	
	Headway (mean, min)	Time headway to vehicle ahead in same lane	s	Only used for tailgating events
	Long. acc. (mean, max.)	Longitudinal acceleration	m/s^2	
Lateral control	Lat. pos. (mean, SD)	Lateral position with respect to dividing lane (right is positive)	m	
	Steer. angle (mean, SD)	Steering wheel angle	degrees	
	Lat. vel. (mean, max.)	Lateral Velocity	m/s	
	Lat. acc. (mean, max.)	Lateral acceleration	m/s^2	
Risk perception	TTC (mean, min)	Time–to–collision with vehicle ahead (for tailgating events) or pedestrian ahead (for VRU events).	s	TTC is used for tailgating events and TTC_ped is used for VRU events (calculated variable).
	Gas displ. (mean, min, SD)	Percentage of max. gas pedal, where 1 is the maximum pressing.	0-1	
	Brake displ. (mean, max., SD)	Percentage of max. brake pedal, where 1 is the maximum pressing.	0-1	
Fixation count	Fixation count (i-DREAMS display)			Not applicable for the monitoring drive, where no interventions are activated
	Fixation count (Road ahead)			
	Fixation count (Dashboard)			
	Fixation count (Pedestrian)			Only applicable for VRU events
Fixation duration	Total fixation duration (i-DREAMS display)			Not applicable for the monitoring drive, where no interventions are activated
	Total fixation duration (Road ahead)			
	Total fixation duration (Dashboard)			
	Total fixation duration (Pedestrian ahead)			Only applicable for VRU events

5.4. Data analysis

This section presents an overview of the analysis for the collected data, including descriptive and inferential statistics for the simulator and eye tracking data (Section 5.4.1), a visualization of the eye movement data (Section 5.4.2), but also an overview on the main results of the questionnaire data (Section 5.4.3). Analysis results pave the way to obtaining first insights on the collected data, with initial points of discussion, that enable the later modeling steps. Parts of the results presented in this chapter are found in Al Haddad, Abouelela, Kris Brijs, et al. (n.d.).

5.4.1. Descriptive and inferential statistics for the simulator and eye tracking data

In this section, an overview of the aggregated results for the selected variables is provided; in essence, for the selected variables, mean values are provided per event and as an average over all 60 participants. Furthermore, an independent two–sample t–test was conducted to compare the change in the selected variables based on the change in the different conditions; namely, the aim was to assess the impact on driving performance and visual attention of different conditions on the one hand (warnings and distraction), and of different safety–critical events on the other hand (differences between different events and event types and related conditions). This can be summarized as follows:

1. A two sample t–test to compare the impact of warnings and distraction on the selected variables. This was conducted by performing pairwise t–tests between the different drives: monitoring, intervention, and distraction. The results for these comparisons are presented in Tables 5.3, 5.4, 5.5[6].
    a) When comparing the monitoring and intervention drives (meaning measuring the direct impact of warnings), following observations were noted, based on the results presented in Table 5.3. For longitudinal control parameters, velocity (both mean and max.) significantly increased in the intervention drive as compared to the monitoring one. Moreover, longitudinal acceleration (mean and max.) increased in magnitude (negative magnitude means here deceleration) for the intervention drive (CE1) as compared to the monitoring one. On the other hand, no significant changes were noted in the lateral control variables between the monitoring and the intervention drives. For risk perception variables, notably minimum time–to–collision, a significant decrease was noted in the intervention drive, as compared to the monitoring one. Similarly, for tailgating events, significant changes were noted in the minimum percentage of gas pedal displaced (a significant decrease in the intervention drive) and in the maximum percentage of brake pedal displaced (significant increase). Finally, both road ahead count and fixation metrics significantly decreased for tailgating events in the intervention drive (maybe as participants were looking more at the display or the dashboard); on the other hand, a significant

[6] Please note that for these tables, abbreviations are used for most simulator variables; the full description of these variables is given in Table 5.2.

increase was noted in the fixation duration and count for the pedestrian area for the VRU events in the intervention drives as compared to the monitoring ones.

b) When comparing the intervention and the distraction drives (meaning measuring the direct impact of distraction), following observations were noted, based on the results presented in Table 5.4. Longitudinal control variables were significantly impacted by distraction; notably maximum velocity significantly increased in some pedestrian events, while it decreased for some tailgating events. On the other hand, metrics for lateral control, in particular those indicating variability, such as the standard deviation of lateral position and of the steering wheel angle, consistently increased for the distraction drives for the different events. When looking at the pedal metrics, a higher standard deviation of the gas pedal displacement was noted for the tailgating events in distraction scenarios, as well as a higher maximum brake percentage for all the events, possibly indicating an increase in braking reaction due to distraction (possibly to compensate the deteriorating driving performance). Finally, when looking at the eye tracking metrics, we noticed a somewhat mixed variation in the fixation count and duration of the i—DREAMS display (higher fixation at the i–DREAMS display for VRU events, but lower for the tailgating events). Moreover, the fixation metrics (both count and duration) on the road ahead, the dashboard, and the pedestrian, consistently decreased (significantly) due to distraction, in all events.

c) By comparing the monitoring drive with the distraction one (though no direct conclusions can come out of that, since two conditions changed between these two drives), the following was observed, based on results presented in Table 5.5: an increase in maximum longitudinal velocity for pedestrian and tailgating events in the distraction drive, as well as a significant change in the longitudinal acceleration. Moreover, as observed when comparing the intervention and distraction drives, a significant change in lateral control was observed, reflected in a significant change in the standard deviation of the lateral position and steering wheel angles, both of which significantly increased in the distraction drive. Also, the gas pedal displacement (SD) significantly increased in the distraction drive, while its minimum value decreased; on the other hand, the maximum brake pedal percentage significantly increased for the distraction drive. Finally, we observed significantly lower fixation (count and duration) on the road ahead, dashboard, and even pedestrian in the distraction drive (less fixation on these areas, possibly due to driver distraction).

Table 5.3.: Two–sample t–test results for selected variables between monitoring and intervention drives

Category	Variable	Potential vulnerable road user interactions									Tailgating scenarios								
		Critical event 1			Critical event 2			Critical event 3			Critical event 1			Critical event 2			Critical event 3		
		Mon.	**Int.**	**t-value**	**Mon.**	**Int.**	**t-value**	**Mon.**	**Int.**	**t-value**	**Mon.**	**Int.**	**t-value**	**Mon.**	**Int.**	**t-value**	**Mon.**	**Int.**	**t-value**
Long. control	Long. vel. (mean)	13.65	14.23	-0.84	9.91	10.28	-0.58	11.21	11.84	-1.32	14.66	15.91	-2.59	20.84	23.89	-2.26	10.91	11.99	-2.47
	Long. vel. (max.)	19.57	20.02	-0.67	14.19	14.13	0.11	14.45	15.09	-1.19	18.96	19.99	-1.30	26.57	30.34	-2.73	13.73	14.74	-1.70
	Headway (mean)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	35.14	23.50	1.23	31.86	25.65	0.38	153.19	64.68	2.35
	Headway (min.)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	16.18	8.57	1.14	17.48	8.75	1.26	14.42	9.16	1.21
	Headway (SD)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	25.31	22.53	0.45	13.54	192.79	-0.94	379.89	77.37	1.72
	Long. acc. (mean)	-0.13	-0.26	2.17	-0.16	-0.23	1.26	-0.13	-0.11	-0.28	-0.05	-0.01	-1.01	0.22	0.25	-0.52	0.02	0.04	-0.96
	Long. acc. (max.)	-3.58	-3.88	0.48	-1.85	-1.33	-0.77	-3.37	-2.19	-1.73	-0.28	-0.98	1.36	0.67	0.12	1.21	-0.32	0.43	-1.42
Lateral control	Lat. pos. (mean)	2.39	2.22	0.82	6.49	6.46	0.59	6.36	6.36	0.01	7.07	7.19	-0.73	11.33	11.74	-1.03	2.13	2.17	-0.18
	Lat. pos. (SD)	0.21	0.15	0.91	0.13	0.14	-0.53	0.15	0.15	-0.17	0.16	0.13	1.07	0.30	0.25	0.57	0.18	0.13	1.13
	Steer. angle (mean)	-0.02	-0.04	0.29	0.09	-0.00	1.04	-0.05	0.01	-0.87	0.03	-0.00	1.30	-0.03	-0.03	0.04	0.10	-0.00	1.50
	Steer. angle (SD)	1.05	1.26	-0.67	1.09	1.26	-0.71	1.29	1.02	1.05	0.74	0.76	-0.11	0.80	0.69	0.65	1.50	1.06	0.96
	Lat. vel. (mean)	0.008	0.001	1.04	0.004	0.004	0.08	0.001	0.00	0.36	-0.001	0.003	-1.25	-0.005	0.002	-0.70	0.006	0.006	-0.01
	Lat. vel. (max.)	0.04	0.04	-0.16	0.03	0.02	0.23	0.01	0.03	-0.46	-0.005	-0.001	-0.08	-0.02	-1.07	0.96	0.03	0.05	-0.57
	Lat. acc. (mean)	0.00	-0.001	1.50	-0.00	-0.00	0.10	-0.001	-0.00	-0.30	-0.00	-0.00	0.06	-0.001	-0.002	0.69	-0.001	-0.00	-0.83
	Lat. acc. (max.)	0.03	-0.07	0.97	-0.02	-0.003	-0.96	-0.03	-0.01	-1.11	-0.05	-0.02	-0.71	-0.06	-0.12	0.67	-0.02	-0.04	0.63
Risk perception	TTC (mean)	184.39	141.98	1.44	238.73	121.29	1.60	468.11	322.72	2.07	334.78	231.14	0.90	361.10	197.81	0.99	1087.72	870.46	0.53
	TTC (min.)	42.96	17.48	1.31	82.26	30.65	1.33	100.68	15.35	2.29	35.60	24.05	0.70	41.74	30.97	0.44	43.07	28.32	0.88
	TTC (SD)	263.30	172.79	1.48	396.43	509.02	-0.58	481.78	409.05	0.67	2675.20	1228.50	1.08	1851.24	1167.14	0.67	7054.92	6096.95	0.26
	Gas displ. (mean)	0.37	0.35	0.92	0.27	0.24	1.33	0.29	0.29	-0.10	0.33	0.36	-1.57	0.54	0.62	-1.69	0.28	0.31	-1.61
	Gas displ. (min.)	0.03	0.01	1.11	0.02	0.01	0.85	0.01	0.02	-0.78	0.02	0.02	0.20	0.19	0.07	2.79	0.01	0.02	-1.71
	Gas displ. (SD)	0.27	0.28	-0.74	0.20	0.19	1.14	0.17	0.18	-0.51	0.20	0.22	-1.70	0.22	0.26	-2.00	0.17	0.19	-1.06
	Brake displ. (mean)	0.11	0.12	-0.59	0.09	0.08	2.00	0.08	0.07	1.33	0.06	0.06	-0.34	0.06	0.06	-0.10	0.06	0.06	-0.00
	Brake displ. (max.)	0.54	0.59	-0.81	0.48	0.35	2.42	0.55	0.39	2.26	0.14	0.23	-2.05	0.11	0.11	-0.00	0.23	0.21	0.56
	Brake displ. (SD)	0.14	0.15	-0.56	0.10	0.07	2.40	0.10	0.07	2.20	0.02	0.03	-1.70	0.01	0.01	0.46	0.03	0.03	0.71
Gaze fixation count	Road ahead	37.90	35.47	0.96	53.68	48.45	1.81	70.18	62.35	1.86	50.47	46.25	1.03	38.00	36.95	0.34	80.97	64.75	2.41
	Dashboard	9.02	8.18	0.67	7.40	7.98	-0.51	12.58	11.28	0.89	11.03	9.55	1.10	7.38	6.05	1.16	12.33	11.22	0.71
	Pedestrian ahead	6.72	8.03	-1.87	11.82	12.17	-0.31	13.15	14.75	-0.97	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Gaze fixation duration	Road ahead AOI	12.85	12.49	0.54	17.32	17.33	-0.01	23.58	23.43	0.12	22.89	18.96	2.37	16.73	15.65	0.98	28.43	23.88	2.02
	Dashboard	2.72	2.50	0.53	2.11	2.29	-0.50	3.46	3.37	0.20	3.27	2.97	0.60	2.04	1.74	0.84	2.91	2.81	0.25
	Pedestrian ahead	2.25	2.77	-2.43	3.41	4.45	-2.17	3.96	5.67	-2.68	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.

Table 5.4.: Two–sample t–test results for selected variables between intervention and distraction drives

Category	Variable	Potential vulnerable road user interactions									Tailgating scenarios								
		Critical event 1			Critical event 2			Critical event 3			Critical event 1			Critical event 2			Critical event 3		
		Int.	Dist.	t-value	Int.	Dist.	t-value	Int.	Dist.	t-value	Int.	Dist.	t-value	Int.	Dist.	t-value	Int.	Dist.	t-value
Long. control	Long. vel. (mean)	14.23	13.77	0.68	10.28	10.72	-1.03	11.84	11.75	0.17	15.91	14.84	2.05	23.89	24.52	-0.51	11.99	11.32	1.34
	Long. vel. (max.)	20.02	20.50	-0.64	14.13	15.57	-2.34	15.09	16.40	-1.62	19.99	20.46	-0.58	30.34	29.26	0.85	14.74	15.72	-1.28
	Headway (mean)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	23.50	180.88	-1.10	25.65	179.05	-0.92	64.68	126.55	-2.41
	Headway (min.)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	8.57	10.61	-0.33	8.75	170.28	-0.97	9.16	13.95	-0.81
	Headway (SD)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	22.53	118.60	-1.23	192.79	7.64	0.97	77.37	348.67	-1.49
	Long. acc. (mean)	-0.26	-0.15	-1.85	-0.23	-0.21	-0.39	-0.11	-0.10	-0.58	-0.01	0.08	-2.35	0.25	0.11	2.66	0.04	0.01	1.36
	Long. acc. (max.)	-3.88	-3.60	-0.43	-1.33	-2.30	1.50	-2.19	-2.25	0.09	-0.98	0.22	-2.09	0.12	-0.34	0.96	0.43	-0.26	1.14
Lateral control	Lat. pos. (mean)	2.22	2.25	-0.21	6.46	6.32	1.28	6.36	6.49	-1.13	7.19	7.16	0.49	11.74	11.92	-0.67	2.17	2.24	-0.29
	Lat. pos. (SD)	0.15	0.27	-2.00	0.14	0.24	-1.59	0.15	0.37	-2.42	0.13	0.25	-2.92	0.25	0.31	-0.76	0.13	0.26	-1.45
	Steer. angle (mean)	-0.04	-0.10	0.64	-0.00	0.09	-0.94	0.01	0.05	-0.73	-0.00	-0.06	1.02	-0.03	-0.10	0.84	-0.00	0.02	-0.64
	Steer. angle (SD)	1.26	2.04	-1.77	1.26	1.89	-2.13	1.02	1.61	-2.68	0.76	1.64	-3.88	0.69	1.12	-2.52	1.06	1.78	-3.24
	Late. vel. (mean)	0.001	-0.008	2.175	0.004	0.008	-1.170	0.000	0.004	-0.941	0.003	-0.002	1.671	0.002	-0.012	1.744	0.006	0.003	1.386
	Lat. vel. (max.)	0.045	-0.128	1.828	0.021	-1.044	0.980	0.026	-2.218	1.449	-0.001	0.002	-0.061	-1.068	-0.134	-0.858	0.050	-2.182	1.441
	Lat. acc. (mean)	-0.001	-0.001	0.144	-0.000	0.001	-1.607	-0.000	-0.001	0.706	-0.000	-0.000	0.219	-0.002	-0.002	-0.268	-0.000	0.001	-0.970
	Lat. acc. (max.)	-0.076	-0.124	0.347	-0.003	0.011	-0.499	-0.010	-0.047	0.804	-0.022	0.056	-0.961	-0.122	-0.144	0.182	-0.045	-0.000	-0.885
Risk perception	TTC (mean)	141.98	224.27	-2.65	121.29	182.39	-1.51	322.72	326.65	-0.12	231.14	724.80	-1.98	197.81	1978.33	-1.14	870.46	384.58	1.47
	TTC (min.)	17.48	21.72	-0.23	30.65	30.38	0.01	15.35	26.69	-0.74	24.05	25.72	-0.13	30.97	249.68	-0.98	28.32	13.22	1.23
	TTC (SD)	172.79	237.24	-2.09	509.02	362.78	0.70	409.05	362.79	0.67	1228.50	4036.57	-1.23	1167.14	22088.48	-1.00	6096.95	1625.90	1.50
	Gas displ. (mean)	0.35	0.35	0.08	0.24	0.25	-0.66	0.29	0.27	0.73	0.36	0.36	0.20	0.62	0.59	0.75	0.31	0.29	1.43
	Gas displ. (min.)	0.01	0.03	-1.05	0.01	0.01	-0.46	0.02	0.02	-0.14	0.02	0.02	-0.28	0.07	0.06	0.35	0.02	0.01	1.25
	Gas displ. (SD)	0.28	0.26	1.12	0.19	0.21	-1.50	0.18	0.21	-1.71	0.22	0.25	-1.74	0.26	0.28	-0.68	0.19	0.22	-2.65
	Brake displ. (mean)	0.12	0.11	1.19	0.08	0.09	-1.48	0.07	0.08	-0.32	0.06	0.06	-0.27	0.06	0.06	-0.21	0.06	0.07	-1.25
	Brake displ. (max.)	0.59	0.58	0.21	0.35	0.46	-2.00	0.39	0.43	-0.52	0.23	0.22	0.21	0.11	0.11	-0.16	0.21	0.31	-2.40
	Brake displ. (SD)	0.15	0.13	0.75	0.07	0.10	-1.79	0.07	0.08	-0.50	0.03	0.03	0.20	0.01	0.01	-0.50	0.03	0.05	-2.66
Gaze fixation count	i-Dreams display	1.10	2.63	-3.53	0.88	3.98	-5.01	1.52	3.65	-3.66	5.22	3.20	2.43	4.73	4.10	0.66	3.02	2.08	1.36
	Road ahead	35.47	33.12	0.86	48.45	39.45	2.86	62.35	42.03	4.47	46.25	32.63	3.39	36.95	31.77	1.68	64.75	31.43	6.61
	Dashboard	8.18	6.82	0.98	7.98	6.48	0.93	11.28	9.30	1.14	9.55	7.07	1.70	6.05	4.63	1.34	11.22	7.05	2.29
	Pedestrian ahead	8.03	4.87	4.20	12.17	8.88	2.60	14.75	7.43	4.27	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Gaze fixation duration	i-DREAMS display	0.25	0.78	-3.14	0.17	1.05	-5.56	0.31	1.03	-4.09	1.18	0.83	1.65	1.36	1.05	0.90	0.59	0.53	0.36
	Road ahead	12.49	11.55	1.25	17.33	13.06	3.82	23.43	14.91	5.23	18.96	10.13	6.60	15.65	11.54	3.93	23.88	10.80	8.50
	Dashboard	2.50	1.86	1.57	2.29	1.57	1.92	3.37	2.46	1.90	2.97	2.05	1.79	1.74	1.16	1.95	2.81	1.88	2.11
	Pedestrian ahead	2.77	1.74	4.79	4.45	2.82	3.06	5.67	2.69	4.19	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.

Table 5.5.: Two–sample t–test results for selected variables between monitoring and distraction drives

Category	Variable	Vulnerable road user scenarios									Tailgating scenarios								
		Critical event 1			Critical event 2			Critical event 3			Critical event 1			Critical event 2			Critical event 3		
		Mon.	**Dist.**	**t-value**	**Mon.**	**Dist.**	**t-value**	**Mon.**	**Dist.**	**t-value**	**Mon.**	**Dist.**	**t-value**	**Mon.**	**Dist.**	**t-value**	**Mon.**	**Dist.**	**t-value**
Long. control	Long. vel. (mean)	13.65	13.77	-0.16	9.91	10.72	-1.30	11.21	11.75	-1.12	14.66	14.84	-0.32	20.84	24.52	-2.84	10.91	11.32	-1.18
	Long. vel. (max.)	19.57	20.50	-1.08	14.19	15.57	-1.87	14.45	16.40	-2.48	18.96	20.46	-1.72	26.57	29.26	-1.91	13.73	15.72	-3.03
	Headway (mean)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	35.14	180.88	-1.02	31.86	179.05	-0.88	153.19	126.55	0.60
	Headway (min.)	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	16.18	10.61	0.79	17.48	170.28	-0.92	14.42	13.95	0.08
	Long. acc. (mean)	-0.13	-0.15	0.45	-0.16	-0.21	0.89	-0.13	-0.10	-0.75	-0.05	0.08	-3.31	0.22	0.11	1.88	0.02	0.01	0.62
	Long. acc. (max.)	-3.58	-3.60	0.03	-1.85	-2.30	0.65	-3.37	-2.25	-1.54	-0.28	0.22	-0.97	0.67	-0.34	2.20	-0.32	-0.26	-0.10
Lateral control	Lat. pos. (mean)	2.39	2.25	0.65	6.49	6.32	1.53	6.36	6.49	-1.13	7.07	7.16	-0.54	11.33	11.92	-1.72	2.13	2.24	-0.58
	Lat. pos. (SD)	0.21	0.27	-0.66	0.13	0.24	-1.71	0.15	0.37	-2.47	0.16	0.25	-2.10	0.30	0.31	-0.14	0.18	0.26	-0.89
	Steer. angle (mean)	-0.02	-0.10	0.85	0.09	0.09	0.04	-0.05	0.05	-1.42	0.03	-0.06	1.44	-0.03	-0.10	0.87	0.10	0.02	1.09
	Steer. angle (SD)	1.05	2.04	-2.76	1.09	1.89	-3.43	1.29	1.61	-1.23	0.74	1.64	-4.34	0.80	1.12	-2.01	1.50	1.78	-0.58
	Lat. vel. (mean)	0.01	-0.01	2.14	0.00	0.01	-1.18	0.00	0.00	-0.72	-0.00	-0.00	0.46	-0.01	-0.01	0.60	0.01	0.00	1.18
	Lat. vel. (max.)	0.04	-0.13	1.99	0.03	-1.04	0.99	0.01	-2.22	1.44	-0.00	0.00	-0.11	-0.02	-0.13	1.39	0.04	-2.18	1.43
	Lat. acc. (mean)	0.00	-0.00	0.88	-0.00	0.00	-1.79	-0.00	-0.00	0.61	-0.00	-0.00	0.16	-0.00	-0.00	0.51	-0.00	0.00	-1.36
	Lat. acc. (max.)	0.03	-0.12	1.64	-0.02	0.01	-1.45	-0.03	-0.05	0.36	-0.05	0.06	-1.22	-0.06	-0.14	0.78	-0.02	-0.00	-0.50
Risk perception	TTC (mean)	184.39	224.27	-1.21	238.73	182.39	0.74	468.11	326.65	2.00	334.78	724.80	-1.60	361.10	1978.33	-1.03	1087.72	384.58	2.53
	TTC (min.)	42.96	21.72	1.00	82.26	30.38	1.35	100.68	26.69	2.01	35.60	25.72	0.73	41.74	249.68	-0.93	43.07	13.22	2.53
	Gas displ. (mean)	0.37	0.35	0.89	0.27	0.25	0.63	0.29	0.27	0.60	0.33	0.36	-1.40	0.54	0.59	-1.15	0.28	0.29	-0.09
	Gas displ. (min.)	0.03	0.03	0.33	0.02	0.01	0.55	0.01	0.02	-0.84	0.02	0.02	-0.11	0.19	0.06	3.24	0.01	0.01	-0.37
	Gas displ. (SD)	0.27	0.26	0.40	0.20	0.21	-0.51	0.17	0.21	-2.22	0.20	0.25	-3.64	0.22	0.28	-2.58	0.17	0.22	-3.80
	Brake displ. (mean)	0.11	0.11	0.64	0.09	0.09	0.42	0.08	0.08	0.89	0.06	0.06	-0.60	0.06	0.06	-0.30	0.06	0.07	-1.24
	Brake displ. (max.)	0.54	0.58	-0.59	0.48	0.46	0.32	0.55	0.43	1.66	0.14	0.22	-2.10	0.11	0.11	-0.16	0.23	0.31	-1.80
	Brake displ. (SD)	0.14	0.13	0.18	0.10	0.10	0.54	0.10	0.08	1.60	0.02	0.03	-1.67	0.01	0.01	0.09	0.03	0.05	-1.82
Gaze fixation count	Road ahead	37.90	33.12	1.87	53.68	39.45	4.82	70.18	42.03	6.56	50.47	32.63	4.36	38.00	31.77	2.05	80.97	31.43	8.75
	Dashboard	9.02	6.82	1.62	7.40	6.48	0.61	12.58	9.30	1.83	11.03	7.07	2.68	7.38	4.63	2.47	12.33	7.05	2.84
	Pedestrian ahead	6.72	4.87	2.66	11.82	8.88	2.65	13.15	7.43	3.96	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Gaze fixation duration	Road ahead	12.85	11.55	1.91	17.32	13.06	4.46	23.58	14.91	6.18	22.89	10.13	8.37	16.73	11.54	4.95	28.43	10.80	9.19
	Dashboard	2.72	1.86	2.17	2.11	1.57	1.54	3.46	2.46	1.98	3.27	2.05	2.53	2.04	1.16	2.73	2.91	1.88	2.36
	Pedestrian ahead	2.25	1.74	2.30	3.41	2.82	1.58	3.96	2.69	2.55	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.

2. A t–test analysis to compare the impact of different conditions (or change in events conditions) on the selected driving performance and eye tracking metrics. For each of the sub–groups, VRU interactions and tailgating events, a pairwise t–test analysis has been conducted between the different events; results for these comparisons are provided in Appendix D.1.
   a) VRU events: an overview of the events as well as a comparison between the different events, notably between between the first (CE1-Ped-Rural) and second (CE2- Ped-Urban) event, the first (CE1-Ped-Rural) and third (CE3-Ped-Urban) event, and between between the second (CE2-Ped-Urban) and third (CE3-Ped-Urban) event, is provided in Tables D.1 , D.2, and D.3 of Appendix D.1.1, respectively.
      i. Comparing the first and second pedestrian events (Table D.1) revealed that longitudinal velocity was overall lower in the urban event, while lateral position was higher. Gas pedal displacement was lower for the urban event, as well as the maximum brake percentage displaced. Finally, eye tracking metrics revealed that in the urban event, fixation on the road ahead was higher, on the dashboard lower, and on pedestrians, significantly higher.
      ii. Comparing the first and third pedestrian events (Table D.2) revealed similar insights; longitudinal velocity (mean and max.) was significantly lower in urban environment as compared to rural; this was also the case for longitudinal acceleration (but not for lateral position which was higher). Similarly, gas pedal displacement and brake pedal displacement significantly decreased for the urban event as compared to the rural one. Finally, insights similar to those observed in Table D.1 were found with respect to eye tracking metrics: overall fixation (both gaze count and total gaze duration) was found to be significantly higher for the urban event for each of road ahead, dashboard, and pedestrian areas, as compared to the rural pedestrian events.
      iii. Between the second and third events (both urban; see Table D.3), a higher longitudinal acceleration (max.) was observed for the latter, as well as a higher longitudinal velocity (both mean and max.). For the eye tracking measures, a higher fixation (count and duration) was noted for CE3 for the dashboard area, the road ahead, but also pedestrian area (except for distraction where a decrease was noted between CE2 as compared to CE3). Results for this comparison are difficult to interpret since they pertain to a comparison between two pedestrian events with a similar environment (both urban).
   b) Tailgating events: a comparison between the tailgating events: basically a comparison between the different environments, rural (CE1-Tail-Rural), highway (CE2-Tail-Highway), and urban (CE3-Tail-Urban) was conducted; a summary of the results is provided in Tables D.4, D.5, and D.6 of Appendix D.1.2.
      i. When comparing the rural and highway environments for tailgating events (Table D.4), a significant increase in longitudinal velocity (mean and max.), longitudinal acceleration (mean) and lateral position (mean) is observed for the

highway events as compared to the rural (probably due to the inherently higher speed limits for highway environments. Moreover, the gas pedal percentage displaced (mean) seems to be significantly higher in the highway environment, whereas the brake percentage significantly lower (also consistent with the nature of the environments). Finally, a significant decrease in the gaze fixation was noted for the events in highway environment (fixation on the road ahead and the dashboard).

ii. Significantly lower longitudinal velocities (mean and max.), acceleration (mean and max.), lateral position (mean), and gas pedal percentage displaced (mean) were noted for urban tailgating events, as compared to the rural ones (Table D.5). On the other hand, a significantly higher steering wheel variability (SD), and brake displacement (max.) were noted for urban as compared to rural tailgating events. Eye tracking metrics revealed a higher fixation gaze for the road ahead in urban events; however, for the dashboard fixation, while fixation count was higher for the urban events, the fixation duration was lower.

iii. Finally, when comparing urban and highway tailgating events (Table D.6), some significant changes (that were expected) were noted: significantly lower longitudinal velocity, acceleration, and lateral position for the urban events (expected as in highway environments, more lane changes happen). On the other hand, a significantly higher steering wheel angle variation was noted for the urban events. Moreover, the gas pedal displacement was significantly lower for the urban events (also expected, due to lower speeds or opportunities of speeding), as opposed to an overall higher brake pedal displacement (max.); the latter also makes sense since on a highway, less harsh braking is expected. Finally, eye tracking metrics reveal higher gaze fixation (both duration and count) for each of the road ahead and the dashboard in the urban environment, as compared to the highway.

5.4.2. Eye tracking dataset visualization

One of the main purposes of eye tracking-based experiments is to provide information about visual attention distribution and its fluctuations for specific stimuli such as distraction in driving simulator studies (Blascheck et al., 2017). Visual tracking devices record gaze coordinates as raw data and then aggregates them into fixations and saccades (AB, 2014; Tobii Pro AB, 2020). For a specific area of interest, this data needs to be visually presentable to provide a quantitative and/or qualitative measure of the attention distribution (Blascheck et al., 2017). In addition to using statistical methods to analyze eye movement data (as done in Holmqvist et al. (2011)), visualization methods are often helpful (Andrienko et al., 2012), to qualitatively visualize the glance behavior intensity; one example is the use of heatmaps (Blascheck et al., 2017). Heatmaps were therefore extracted using the Analyzer module of the eye trackng glasses; in essence, the heatmaps assist in visualizing the aggregated gaze behavior (both fixation and count) for all participants (N=60) for the different scenarios[7]. For each drive scenario, six aggregated heat maps were obtained (to directly visualize the change induced by distraction), each of them corresponding to one safety-critical event. Heat maps use color distributions to display the duration and number of fixations subjects made within a specific AOI; the distribution ranges from red (highest fixation count and longest fixation duration) to green (least count and duration). In this section, a visualization based on the total fixation duration is presented, and as done in Beraneck, Lambert, and Sadeghi (2014).

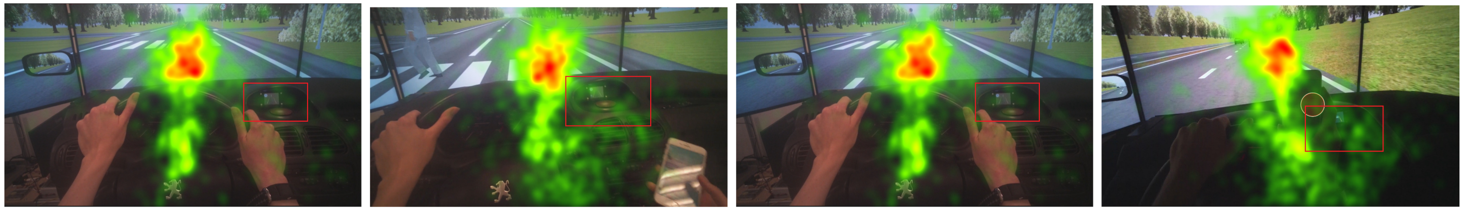
Figures 5.3, 5.4, and 5.5 present the gaze aggregations during potential vulnerable user interactions and tailgating scenarios for the intervention and distraction drives[8], assisting in visualizing the changes induced by distraction in the third drive. The heatmaps show that during distraction (as compared to the intervention scenario), drivers' gazes tend to be more spread over the different areas of interest, notably the intervention system (marked by a red square). In other words, we can visually see that drivers' attention is more "divided" during distraction, irrespective of the safety–critical event or of the driving environment.

[7]It should be noted that heatmap exports are normally provided on a black background by Tobii Pro Lab. For the sake of visualization, heatmaps representing the aggregate glance data over the events of interest have been transposed on an individual snapshot of the driving environment during a moment in the corresponding safety-critical event (otherwise, this would be on an empty background, which would not be easy to grasp).

[8]For a description of the critical events, please refer to Table A.3 of Appendix A.2

(a) CE2, intervention scenario (b) CE2, distraction scenario (c) CE6, intervention scenario (d) CE6, distraction scenario

Figure 5.3.: Heat maps for gaze distribution during CE2 (vulnerable road user interaction) and CE6 (tailgating scenario) in the urban context



(a) CE1, intervention scenario (b) CE1, distraction scenario (c) CE4, intervention scenario (d) CE4, distraction scenario

Figure 5.4.: Heat maps for gaze distribution during CE1 (vulnerable road user interaction) and CE4 (tailgating scenario) in the rural context (N=60)

(a) CE3, intervention scenario (b) CE3, distraction scenario (c) CE5, intervention scenario (d) CE5, distraction scenario

Figure 5.5.: Heat maps for gaze distribution during CE3 (vulnerable road user interaction) in the urban context and CE6 (tailgating scenario) in a highway environment (N=60)

5.4.3. Questionnaire data analysis

In addition to getting first insights on the driving simulator and eye tracking datasets, assessing drivers' responses to the different questionnaires is crucial to better understand their initial attitudes and perceptions towards driving, driving safety, ADAS, but also their feedback, perceptions, and acceptance of the system they experienced, namely the i–DREAMS system. In this sub–section, a descriptive analysis of the questionnaires results is provided, with initial statistics on demographics' impacts on various attitudes. After that, a qualitative analysis of the questionnaires' open–ended questions was conducted, to further explore participants' experiences.

1. Descriptive analysis
   The descriptive questionnaire analysis consists of an analysis of responses to the entry questionnaire and to the first exit questionnaire (Exit A). After aggregating the results over participants, average values for the different constructs were visualized. Only when otherwise significant, a differentiation by gender is shown. Figures 5.6 to 5.8 present participants' attitudes towards ADAS, towards the i–DREAMS system, but also towards the system clarity. Additional plots representing participants' exposure to ADAS (availability in their vehicles and frequency of use), perceptions with regards to distraction engagement and driving are presented in Appendix D.2.1.

   Furthermore, an assessment of the impact of demographics on various perceptions was made; in particular, the impact of gender[9] was investigated, using Chi-square tests, with a 95% confidence level. Overall, the Chi-square tests showed that gender did not impact significantly the constructs of ADAS presence, frequency of use, perceptions towards ADAS, overall attitudes towards distraction engagement, driving, but also attitudes towards the i-DREAMS system. The Chi–square results for gender and other attitudinal variables are presented in Appendix D.3.1.

   In the entry questionnaire, participants' attitudes towards ADAS in general were assessed, with insights on their perception of ADAS usefulness, ease of use, but also potential distracting effect they might have on driving. Figure 5.6 presents a summary of these findings for the different statements, which had five response options, ranging from "strongly disagree" to "strongly agree". For the below summary, the term "agree" will be used as a simpler way to refer to both answer options "strongly agree" and "agree", whereas the term "disagree" would be used as a simplification for "strongly disagree" and "disagree". In general, most respondents seemed to agree that ADAS are useful (about 95%) and are a good idea (about 90%), and that they have benefits [help maintaining safe driving (above 80%), decrease accident risk (above 70%)]. The majority also seemed to trust the information received from ADAS (above 60%), and feel comfortable doing other things with ADAS (above 50%). Moreover, most respondents found ADAS information clear and ADAS easy to use (above 65%). Overall, participants had therefore rather positive feedback towards ADAS, with only a lower percentage

[9]Based on Table 5.1, only gender was a suitable variable for the Chi–square tests of independence, as it was the only balanced categorical variable that could be used for comparison.

believing that ADAS itself might be distracting (about 15%) or might require increased attention (less than 15%).

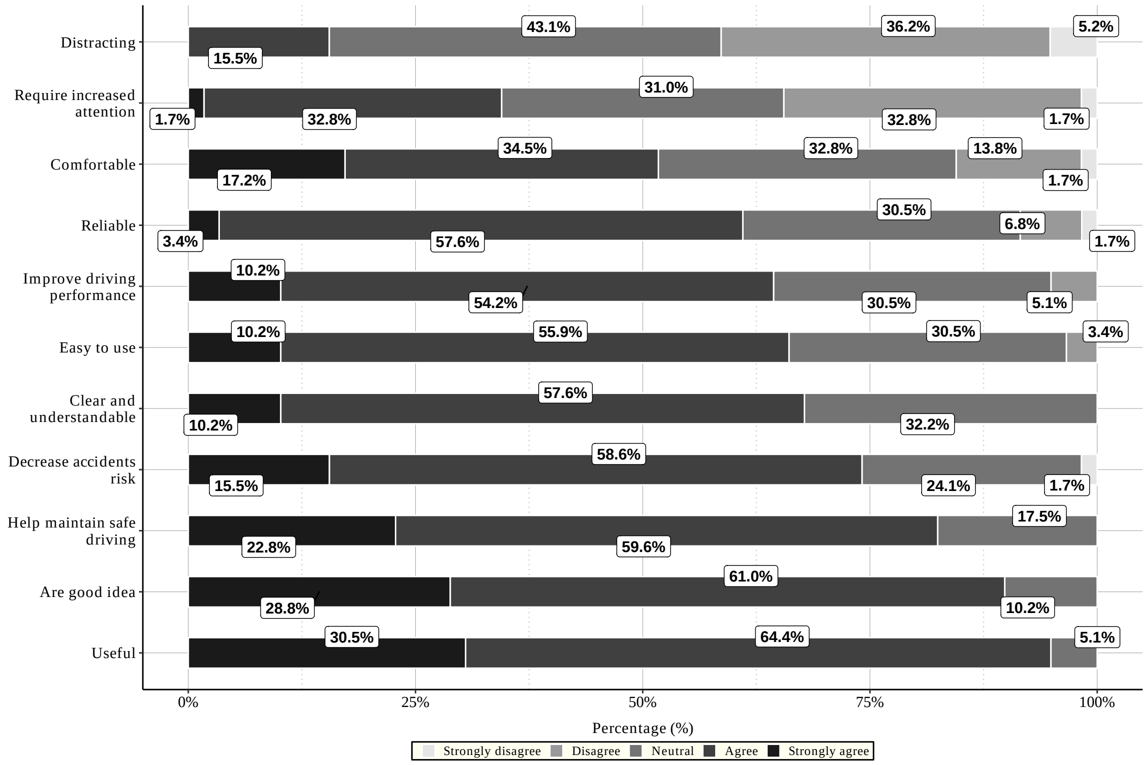


Figure 5.6.: Car participants' overall attitudes towards ADAS (N=60)

Figure 5.7 presents a summary of the findings of participants' attitudes towards the i–DREAMS system, based on the first exit questionnaire (Exit A), collected after the first set of driving experiments. The main findings suggest that participants mostly agree that the i–DREAMS system is a good idea (about 80%), which helps them to maintain safe driving (about 75%) or reach their destinations safely (also make them safer drivers–above 50%), and allows them to multi-task while driving. Most participants would rely on the system, and believe it would make them more aware of their surroundings, would recommend it to others, and continue using it if given the choice (about 60%). Moreover, most respondents seemed to agree that the system is easy to use (about 85%), and that they have the knowledge necessary to use it (above 80%). A lack of consensus however was found on whether or not the system required increased attention (about 45% neutral), and whether participants would be proud to show it to others (about 30% neutral), or whether they believed others would encourage them to use it (above 40% neutral). Finally, most participants seemed to disagree that the system distracts them (about 65%), annoys them (about 75%), or negatively affects their driving performance (above 75%).

Overall, perceptions towards the system were quite positive, with participants believing it to be useful and easy to use (above 80%); however, overall, the level of acceptance seemed to be rather lower than the one of the ADAS in Figure 5.6, which makes sense since the latter refers to participants' overall ADAS perceptions, while the former refers to the newly experienced system (within the scope of the experiments).

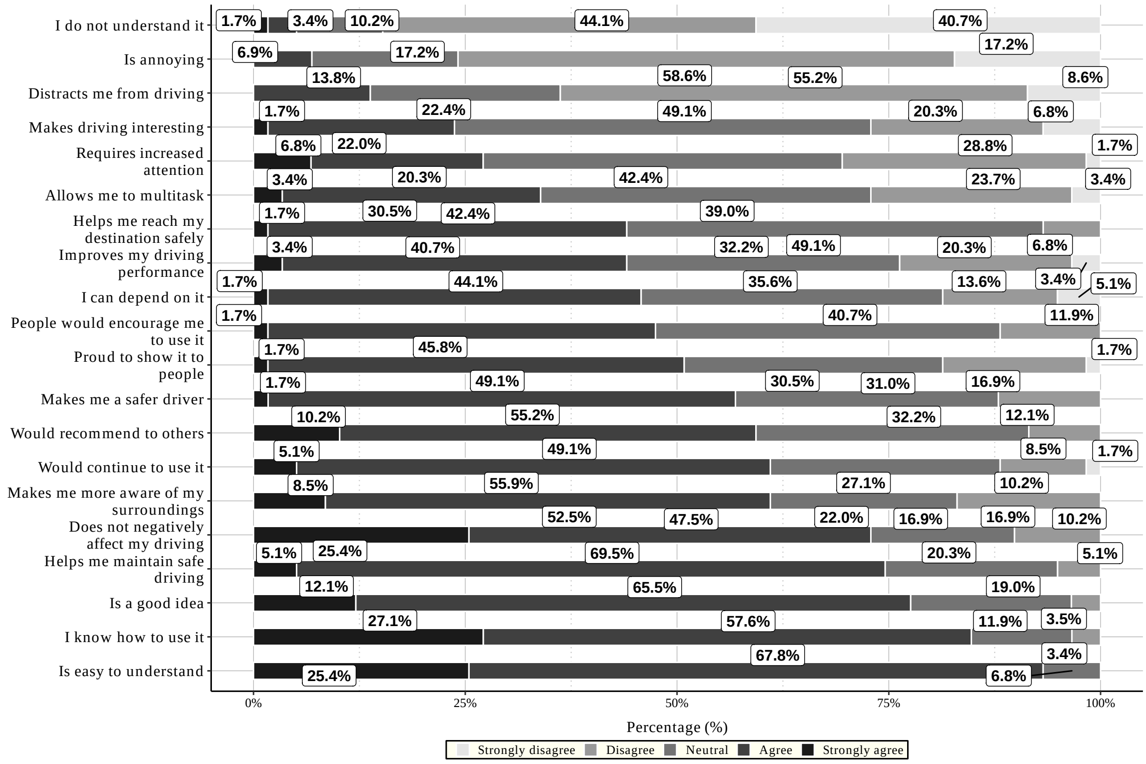


Figure 5.7.: Car participants' overall attitudes towards the i-DREAMS system (N=60)

Figure 5.8 presents a summary of the findings on participants' perceptions of the i–DREAMS system clarity. Overall, 88% of participants found the system generally clear (a combination of "very clear" and "clear" answer options). Similarily, 88% of participants found the system to be visually clear (based on the visual symbols). On the other hand, only 45 % found the sounds of the i–DREAMS system to be clear (combination of "very clear" and "clear"). These results reflect the findings from the qualitative analysis, in which respondents indicate that they understand the system overall, mostly the visual components, but also indicate some limitations or improvement potentials in the sounds of the different warnings.

2. Qualitative analysis
In this section, a qualitative analysis is presented based on the open–ended questions of

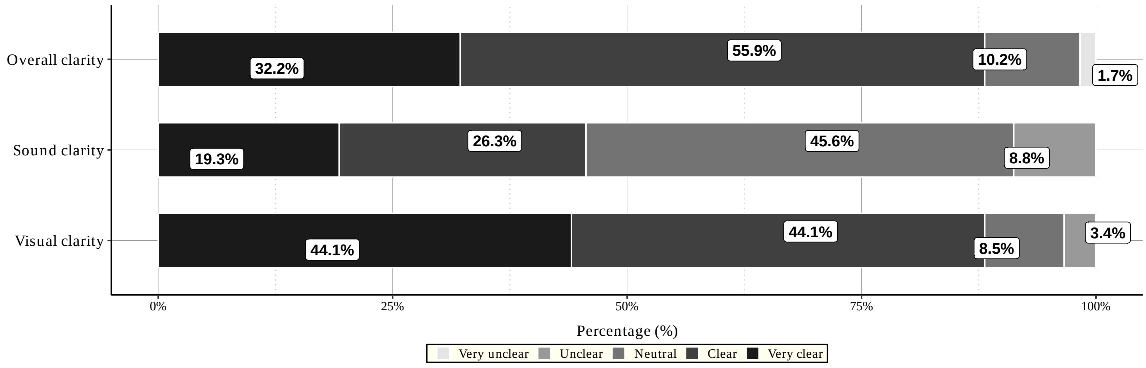


Figure 5.8.: Car participants' overall perceptions of the i–DREAMS system clarity (N=60)

the questionnaires (Exit A and Exit B). These concern the main strengths of the system, the recommended improvements, the general impressions about the system (positive and negative keywords), and finally its clarity (general, visual, and sound clarity). When it comes to the strengths, most comments indicated that the system was found to be quite useful, by increasing driver's safety, and maintaining driving awareness. It was also perceived as quite useful, easy to understand, and user–friendly. Visual graphics were clear, auditory sounds were understandable, and the simulator design was realistic. Finally, the warning system including the time indication (time remaining before hitting the obstacle) was perceived as quite useful, and quick enough (to alert).

However, participants indicated some measures which could improve the system. Notably, the screen where the warnings were displayed was perceived to be too far and too small. With regards to the sound assistance, more sounds or a voice notification announcing the warnings to come would be appreciated; another tip was for instance to announce exceedance of speed limit, or upcoming danger. It was also noted that some warnings could be improved, notably the distraction warning, the pedestrian collision warning, and the over–speeding warning. Another suggestion was to remove (as they were perceived as distracting) the numbers from the pictograms (seconds to collisions) and replace them by the corresponding distance.

The main keywords used to describe the system were positive and can be summarized as follows: easy, clear, visually appealing, useful, safe, and convenient. On the other hand, some comments pointed out that the system was acoustically incomplete (lacking perhaps some sound functionalities such as a voice over warning) or even distracting. Overall, the system was found to be easy to understand and therefore quite clear: symbol colors were understandable as they resembled existing systems. As mentioned above, some warnings were triggered a bit too late, and a voice over warning could be useful. A vibrating steering wheel was also suggested as a further improvement.

Regarding visuals, icons and graphics were seen as simple to understand. On the other hand, sound clarity while for most was adequate, for others, sounds seemed to be a bit too loud and sometimes even distracting, or not understandable. More differentiation between the sounds was also noted as a suggestion. A longer testing phase where warnings are explained (sounds wise) would be useful; on the other hand, this might lead to biases in the driving performance and scenario predictability.

6. Modeling Results

This chapter presents the models developed based on results obtained and discussed in Chapter 5. Excerpts of this chapter are found in Al Haddad, Abouelela, Kris Brijs, et al. (n.d.) and Al Haddad, Abouelela, Graham Hancox, et al. (2022). In particular, results are modeled to i) understand drivers' attitudes and perceptions and acceptance of the system they experienced, ii) understand the impact of various factors on driving performance based on selected variables (including driving simulator, eye tracking data, and questionnaire data).

6.1. Drivers' perceptions and acceptance models

Modeling drivers' attitudes and perceptions essentially relies on using the questionnaire data, and exploring whether some of the variables resulting from agreement statements or constructs have any underlying meaning that can help in making a better use of this data. The aim of this section is therefore to on the first hand extract these variables, and on the other hand use them in order to test the hypotheses of interest in relation to the system's acceptance. The former will be done by means of exploratory factor analyses, while the latter would be reached by testing hypotheses drawn in Section 3.3, in relation with the technology acceptance model. Finally, a discussion of the findings can help shed light on the main insights obtained from this analysis.

6.1.1. Exploratory factor analysis

As mentioned in Section 3.2.1, exploratory factor analyses can be used as methods to reduce the dimensionality of questions that have the same response option scales, which can assist in revealing hidden patterns or uncovering latent variables behind this set of similar constructs. In particular, for the questionnaires of the driving simulator experiments, each of the entry and exit questionnaires had a set of constructs, to which such analyses could be useful; five–point Likert scale agreement statements were grouped in three analyses of interest: participants' initial perceptions of ADAS (based on the entry questionnaire), participants' attitudes on distraction engagement while driving (based on the entry questionnaire), and participants' perceptions of the i–DREAMS system (based on the exit questionnaire). The analyses results are presented in Tables 6.1, 6.2, and 6.3, based on the constructs presented in Figures 5.6, D.3 to D.6, and 5.7, respectively.

For all analyses, the maximum likelihood estimation was used as a factor extraction method. Moreover, a scree test was performed to determine the optimal number of factors, and since the factors were assumed to be uncorrelated, *varimax* orthogonal rotation was used (H. F. Kaiser, 1958). Factor scores were then computed using a weighted sum of the factor loads. Variables for which loadings were higher than 0.4 were retained and factors that could explain more than 10% of the variance were considered acceptable [Costello and Osborne (2005)].

For the first factor analysis (Table 6.1), factors extracted were interpreted as ADAS ease of use and ADAS usefulness. The former is a combination of "easy to understand" and "clear and understandable" (accounting for 27% of the data variance), while the latter is a combination of "useful", "reduces accident risks", and "trust ADAS information" (accounting for 21% of the variance); the cumulative variance represented by both factors corresponds to 48%.

Table 6.1.: Factor analysis results of car participants' perceptions of ADAS

Loadings	Factor 1	Factor 2
ADAS are easy to understand	0.84	
ADAS are clear and understandable	0.77	
ADAS are useful		0.70
ADAS reduces accident risks		0.61
I trust ADAS information		0.41
Sum of square of loadings	1.34	1.05
Proportion variance	0.27	0.21
Cumulative variance	0.27	0.48
Factor interpretation	ADAS ease of use	ADAS usefulness

Distraction attitudes were grouped under two main factors (Table 6.2). The first factor corresponds to engagement in secondary distraction, including the belief of being able to drive well while eating or drink and while conversing with passenger, the perception that it is okay to drive while eating or drinking, and the perception that these activities are distracting (for the latter construct, a negative sign was observed, which makes sense since it is the meaning is opposite in comparison with the other constructs). This factor represents 30% of the data variance. The second factor corresponds to phone distraction, combining a set of factors on beliefs and perception of driving well or thinking it is okay to drive while interacting with the phone, or conversing with the phone. This factor represents 21% of the variance. In total, both factors make up to 51% of the data variance for these constructs.

Table 6.2.: Factor analysis results of car participants' attitudes on distracted driving

Loadings	Factor 1	Factor 2
Believe to drive well while eating andor drinking	0.91	
Believe to drive well while conversing with passengers	0.71	
Think it is okay to drive while eating andor drinking	0.62	
Find it distracting to drive while reading roadside advertisements	-0.50	
Find it distracting to drive while conversing with passengers	-0.64	
Find it distracting to drive while eating andor drinking	-0.71	
Believe to drive well while conversing with the phone		0.56
Believe to drive well while interacting with the phone		0.61
Think it is okay to drive while interacting with the phone		0.73
Think it is okay to drive while conversing with the phone		0.86
Sum of square of loadings	3.03	2.08
Proportion variance	0.30	0.21
Cumulative variance	0.30	0.51
Factor interpretation	Secondary distraction	Phone distraction

For the final factor analysis, focusing on participants' perceptions of the i–DREAMS system (Table 6.3), two main factors were extracted, namely the i–DREAMS system perceived usefulness and the i–DREAMS system perceived ease of use, representing 31 % and 14% of the total variance, respectively, a cumulative 45% of the data variance. The former factor is a combination of various constructs including the system's usefulness, the perception that it is a good idea, that it makes drivers more aware of their surroundings, that it makes them safer drivers, and that it improves their driving performance, etc. The latter factor is a combination of constructs reflecting the system ease of use; this includes a negative loading for the third construct ("I am afraid I do not understand the system"), which makes sense as it is opposite in meaning to the other variables this factor is based on.

Having obtained the factor analysis results summarized in Tables 6.1, 6.2, and 6.3, new factors scores were generated as a linear combination of the factor loadings and variables for which the factors loaded, using a weighted sum of the factor loads.

Table 6.3.: Factor analysis results of car participants' perceptions of the i–DREAMS system

Loadings	Factor 1	Factor 2
Using the i–DREAMS system is a good idea.	0.72	
Using the i–DREAMS system makes me more aware of my surroundings	0.69	
The i-DREAMS system makes me a safer driver	0.69	
The i-DREAMS system improves my driving performance	0.66	
I would be proud to show the i-DREAMS system to people close to me	0.65	
While using the i-DREAMS system, I can maintain safe driving behavior.	0.62	
People who I like would encourage me to use the i-DREAMS system	0.59	
Using the i-DREAMS system, I will reach my destination safely	0.55	
The i-DREAMS system makes driving more interesting.	0.55	
I have the knowledge necessary to use the i-DREAMS system.		0.77
I think the i-DREAMS system is easy to understand		0.50
I am afraid that I do not understand the system.		-0.71
Sum of square of loadings	3.68	1.71
Proportion variance	0.31	0.14
Cumulative variance	0.31	0.45
Factor interpretation	Perceived usefulness	Perceived ease of use

6.1.2. Technology acceptance model hypothesis testing

This section presents the results of the models developed to test the hypotheses presented in Figure 3.1. To test the first hypothesis, or in other words that the intention to use of the i–DREAMS system is a function of its perceived ease of use and perceived usefulness, the "usage" variable ("I would continue to use the i–DREAMS system) was used as the "behavioral intention" (BI) of the technology acceptance model. For the independent variables, or in other words the perceived ease of use (PEU) and perceived usefulness (PU) of the system, the newly generated factors resulting from the factor analysis presented in Table 6.3 were used. Since the dependent variable ("usage") is a discrete outcome with answer options ranging from "strongly agree" to "strongly disagree", or in other words ordinal discrete responses, the hypothesis was tested by developing an ordinal logit model with the variables mentioned (usage as dependent variable, ease of use and perceived usefulness as independent variables). For this model, and since the responses were unbalanced, the five answer options were regrouped in three categories: disagree (including "strongly disagree" and "disagree"), neutral, and agree (including "strongly agree" and "agree"). The model results are presented in Table 6.4.

Results of the above model highlight that the perceived usefulness and ease of use of the i–DREAMS system are highly significant factors (95% confidence level) that impact the intention to use the system (Hypothesis 1). The positive sign also indicates that the higher the perceived usefulness and perceived ease of use of the i–DREAMS system, the higher the chance of intending to use it in the future, which again is consistent with hypothesis 1.

For the second hypothesis, PU was used as a dependent variable, in order to test its relationship with both PEU, but also other external variables. For this model, an ordinary

Table 6.4.: Ordinal logit model estimate results for car participants' intention to use the system

Variable	Estimate	t–test	Sig.
Perceived usefulness	2.11	4.63	***
Perceived ease of use	0.66	2.04	*
Disagree | Neutral	-3.41	-5.11	***
Neutral | Agree	-0.59	-1.60	
Log–likelihood = -34.7			
AIC = 77.5			
BIC = 85.8			
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**			

least square regression model was developed due to the ordinal and continuous nature of the dependent variable in question. The model results are presented in Table 6.5.

Table 6.5.: Ordinary least squares estimate results for car participants' perceived usefulness of the system

Variable	Estimate	t–test	Sig.
Intercept	-0.010	-0.083	
ADAS perceived usefulness	0.33	2.67	**
R squared	0.11		
Adjusted R–squared	0.09		
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**			

Results of the model presented in Table 6.5 did not indicate a strong and significant relationship between the perceived usefulness and perceived ease of use of the i–DREAMS system. On the other hand, only perceived usefulness of ADAS (factor resulting from the factor analysis presented in Table 6.1) was found to be significant (among other external variables) in impacting the perceived usefulness of the i–DREAMS system. This means that the second hypothesis is only partially validated.

Finally, the third hypothesis was tested. Among other external variables, gender was used, in addition to the newly generated attitudinal factors resulting from the factor analyses presented in Tables 6.1 and 6.2, indicating participants' attitudes and perceptions towards ADAS and distraction engagement while driving, respectively. To examine the relation postulated in this hypothesis, and since the perceived ease of use is a continuous variable (whose values was computed as a linear combination of the factor loadings and different variables as per the factor analysis results), an ordinary least square model (OLS) was developed; the results of this model are presented in Table 6.6.

Results presented in Table 6.6 highlighted the impact of only one external variable in relation to the i–DREAMS' system perceived ease of use, the duration or time period for which the participant has obtained his or her driver's license. In particular, this negative relation indicates that the higher this duration is, the lower the perceived ease of use of the i–DREAMS system. This could be attributed to the fact that the higher the license duration,

Table 6.6.: Ordinary least squares estimate results for car participants' perceived ease of use of the system

Variable	Estimate	t–test	Sig.
Intercept	0.41	2.08	*
Driver's license duration (years)	-0.034	-2.65	**
R squared	0.11		
Adjusted R–squared	0.09		

Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

the older the participants, and therefore the (possibly) lower affinity to newer technologies, which could explain the negative correlation with the perceived system ease of use. Still, this means that the third hypothesis is validated, as external variables such as the license duration significantly impacted the system's perceived ease of use.

6.2. Panel regression models: an integration of various datasets

The resulting and merged dataset consisted of highly heterogenous variables from different sources: the driving simulator, the eye tracking glasses, and the different questionnaires (demographics, attitudes, newly generated attitudinal variables from the factor analysis). To understand the factors impacting different driving performance metrics for different safety–critical situations, various models were developed for each of the tailgating and VRU events. To have a rich dataset, observations were merged across the three drives, with newly created dummy variables for warnings (whether there were warnings or not) and distraction (presence of distraction or not), to label or indicate the condition of the drive (basically to differentiate the first, second, and third drives from each other). Therefore, for each of the 60 participants, and for each critical event , 180 observations were available after merging the drives (60*3). Variables of interest for VRU events were selected as the minimum time–to–collision, the variability of the gas pedal percentage pressed, the maximum brake pedal percentage pressed, and the absolute value maximum longitudinal acceleration (the maximum across both acceleration and deceleration variables). For tailgating events, additionally, the minimum time headway was a variable of interest. The aim was therefore to investigate how different conditions (driving, environment, driver—specific) would impact the selected driving performance variable; the variables to investigate would be used as independent variables in the developed panel regression models. Of course, the initial data analysis and inferential statistics for the simulator and eye tracking data paved the way into better understanding the variables that were significantly impacted as a result of the intervention–system or of distraction. This was therefore taken into account for the models to follow and would be used to see whether the model results consistently reflect the findings of these statistics.

As the same individuals participated in different safety–critical events and therefore various observations were repeated across the same individuals, panel regression models were considered to be suitable; models of interest considered individual effects only, as time effects were not of interest for the studied dataset (the repetition across drives does not really span across time and the repetition impact is also taken care of in the experimental design by randomly changing the order of events across the drives). Random effect models were first developed and considered. Then, to validate their adequate use, various tests were conducted, by comparing them with fixed-effect models, or no-effects/pooled (or simply put OLS) models. The models were developed for each critical event separately at first (a maximum of 180 observations per model), then for a dataset containing all events per category (e.g. all 3 VRU events merged at once, or all 3 tailgating events merged at once, a maximum of 540 (180*3) observations, for which the specific events (e.g. CE1, or CE2), and thereby the resulting driving environment, were used as a dummy variable. A summary of the best performing models is given below in sub–sections 6.2.1 and 6.2.2, for VRU and tailgating models, respectively.

6.2.1. VRU models

In the below sub–section, VRU events model results and a preliminary interpretation are given, with the following selected dependent variables: log(TTC_{min}), maximum brake pedal pressing percentage, gas pedal pressing percentage variability, absolute value of maximum longitudinal acceleration.

1. log(TTC_{min}):
   As TTC_{min} was rather unbalanced for VRU events, the logarithmic value of this variable was used instead [log(TTC_{min})]; see a distribution of these variables [both TTC_{min} and log(TTC_{min})] in Appendix D.2.3. Models were then developed using log(TTC_{min}) as a dependent variable for each of the VRU events (CE1, CE2, CE3, but also a merged dataset with all events). A summary of the results is found in Table 6.7.

   For CE1, various variables were found to positively impact log(TTC_{min}), and therefore TTC_{min}[1], including longitudinal velocity (mean), and lateral velocity (mean), whereas lateral position (SD) was found to negatively impact TTC_{min}. For CE1, the no–effects model was found to be better than the random effect models, for which individual effects were found to account for about 17% of the variance. For CE2, the no–effects model was found to be best, but was in fact the same as the random–effects model, for which individual random effects were null (0%). For this model, the absolute value maximum longitudinal acceleration was found to positively impact TTC_{min}, whereas lateral position (mean) and steering wheel angle (SD) were found to negatively impact TTC_{min}. A higher pedestrian fixation count was found to be positively related with a higher TTC_{min}, which makes sense, as drivers who stare longer on pedestrians, are expected to have focused more, enough to keep a higher distance from them, and which is detected in a higher TTC_{min} value. Finally, age was found to negatively impact TTC_{min}

[1]For the remainder of this section, and for the sake of simplicity, TTC_{min} will be used instead of log(TTC_{min}), as an impact on one is likely to impact the other directly.

for this event; in other words, older participants had a higher tendency to keep a lower gap with the pedestrian crossing.

For CE3, the random–effects model was found to be best (although random effects did not prove to be significant), for which random individual effects accounted for about 8%; significant values obtained in this model were the absolute value maximum longitudinal acceleration. Finally, for the model using all events, the random–effects model was found to be the best, with about 13% of the effects being individual. Maximum longitudinal acceleration was found to be significantly related to a lower TTC_{min}, whereas maximum longitudinal deceleration and both lateral velocity (mean) and position (mean) were found to be positively related with a higher TTC_{min} value. The presence of warnings (so the interventions being activated) seemed to be related with a lower TTC_{min}, whereas a rural environment seemed to have the opposite impact (higher TTC_{min}).

Overall, for VRU events, it seemed that significant variables for the TTC_{min} were longitudinal control indicators (acceleration and velocity), lateral control parameters (lateral position, steering wheel angle), the presence of warnings, the type of environment (rural), and pedestrian gaze fixation.

2. Brake pedal percentage displaced (max.):
Model results for this variable are listed in Table 6.8 (for CE1 and CE2) and Table 6.9 (for CE3 and the merged dataset). For the model using the CE1 dataset (Table 6.8), the random–effects model was found to be the best (with 13% of the effects being individual), with significant variables obtained being longitudinal control parameters (maximum deceleration and mean velocity) which were negatively associated with the maximum brake pedal percentage displaced, but also lateral control ones, including mean deceleration (positive relation), lateral velocity (mean) and position (mean), both having a negative impact on the maximum brake pedal displaced. From the condition variables, distraction seemed to positively impact the brake pedal displacement, and gender (females vs. males) seemed to also be a significant variable (females having a tendency to press less on the brake pedal as opposed to males).

For CE2 (Table 6.8), the random–effects model was found to be the best as well, with 22% of the random effects attributed to individual ones. Here, longitudinal velocity (max.) and perceived ease of use for the system, were both found to be highly significant in impacting the brake pedal displacement. For CE3 (Table 6.9), the fixed–effect models were found to be best, followed by the no–effect models, whose estimates were quite close in magnitude to the random–effects model (that only had 2% of random effects coming from the individual ones). Longitudinal acceleration (mean) and deceleration (max.), as well as lateral deceleration (mean) and lateral position (mean) all had negative estimates, meaning they were negatively associated with a higher increase in brake pedal displacement.

Finally, for the model applied on the entire VRU observations dataset (Table 6.9), the fixed–effect was found to be the better model in comparison. Most significant variables had a negative impact on the maximum brake percentage displacement: notably, longitudinal control variables [longitudinal control acceleration (mean), deceleration (max.), and velocity (mean)], lateral control variables [lateral velocity (mean) and lateral position (mean)], and finally the driving environment (rural).

3. Gas pedal percentage displaced (SD):
For both CE1 and CE2 (Table 6.10), the random–effects model was found to be better (for the latter, individual effects accounted for about 17% of the total random effects). For both models, longitudinal velocity (maximum) had a positive impact. Additional significant variables obtained were longitudinal acceleration (mean and maximum), deceleration (mean, maximum), lateral acceleration (mean), and lateral position (mean). For CE3 (Table 6.11), the no–effects model was found to be the better model, followed by the fixed effects one, then the random–effects model; this is also noted from the R–squared values (the R–squared for the random–effects model is quite low in comparison with those of the fixed effects and no–effects models). Variables that were highly significant are longitudinal acceleration (maximum), velocity (mean), but also gender (females as compared to males tending to have a lower gas pedal displacement variability).

   Finally, for the model merging all events (Table 6.11), the random–effects model performed best. Longitudinal acceleration (maximum) and velocity both yielded positive estimates, as opposed to deceleration (mean) and lateral position (SD), whose estimates were negative. Moreover, distraction as a condition seemed to be highly significant for the gas pedal percentage displacement variability (negative relation). Finally, the urban environment seemed to play a positive role in the gas pedal displacement variability, as compared to other road environments.

4. Longitudinal acceleration [Abs(max.)]:
Results of these models are given in Table 6.12. For the different models (CE1, CE2, CE3, or merged events), the random effect model proved to be the best. For CE1, significant variables were longitudinal velocity (maximum), lateral position (mean) and perceived usefulness of ADAS. The total random (individual) effects of the model amounted to 16.5%. For CE2 (23% individual random effects), the longitudinal velocity (maximum) was also found to be significant, as well as the perceived ease of use of ADAS. For CE3, in addition to the longitudinal velocity (maximum), the steering wheel angle variability was highly significant. Moreover, the presence of warnings also seemed to have a high impact on harsh acceleration; finally, gender was also found to be quite impactful.

   The merged model also revealed that the random–effects model was the better performing model, with 13% of the effects owing to individual variability. Highlighted significant variables were: longitudinal velocity (max.), perceived ease of use of the i–DREAMS system, and finally the environment (urban as opposed to rural).

Table 6.7.: VRU panel model results using $\log(TTC_{min})$ as a dependent variable

Critical event 1

	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-3.49	0.51	-6.84	***	-3.60	0.52	-6.94	***
Long. vel. (mean)	0.083	0.032	2.56	*	0.089	0.032	2.74	**
Lat. vel. (mean)	10.20	3.64	2.80	**	10.15	3.62	2.81	**
Lat. pos. (mean)	1.11	0.12	8.95	***	1.12	0.12	9.26	***
Lat. pos. (SD)	-1.06	0.34	-3.13	**	-1.07	0.34	-3.19	**
					Random effects			
					$\sigma^2[e] =$	2 (83%)		
					$\sigma^2[u] =$	0.41 (17%)		
	Model fit				**Model fit**			
	Observations: 179				Observations: 179			
	R-Squared: 0.39				R-Squared: 0.41			
	Adj. R-squared: 0.37				Adj. R-squared: 0.39			
Hausman test			*0.91*					
Breusch-Pagan Lagrange Multiplier Test			*0.06*					

Critical event 2

	Random effects			
	β	SE	t-value	Sig
Constant	6.29	1.58	3.97	***
Abs. Long. acc. (max.)	0.12	0.032	3.76	***
Lat. pos. (mean)	-0.60	0.24	-2.51	*
Steer. wheel angle (SD)	-0.29	0.081	-3.52	***
Pedestrian fix. count	0.030	0.018	1.67	.
Age	-0.025	0.013	-1.95	.
	Random effects			
	$\sigma^2[e] =$	2.624 (100%)		
	$\sigma^2[u] =$	0 (0%)		
	Model fit			
	Observations: 180			
	R-Squared: 0.21			
	Adj. R-squared: 0.19			
Hausman test			*0.95*	
Breusch-Pagan Lagrange Multiplier Test			*0.37*	

Critical event 3

	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	1.66	0.16	10.52	***	1.65	0.17	9.90	***
Abs. Long. acc. (max.)	0.22	0.034	6.30	***	0.21	0.035	6.10	***
					Random effects			
					$\sigma^2[e] =$	2.78 (92%)		
					$\sigma^2[u] =$	0.24 (8%)		
	Model fit				**Model fit**			
	Observations: 178				Observations: 178			
	R-Squared: 0.18				R-Squared: 0.17			
	Adj. R-squared: 0.18				Adj. R-squared: 0.17			
Hausman test			*0.17*					
Breusch-Pagan Lagrange Multiplier Test			*0.31*					

Merged events

	Random effects			
	β	SE	t-value	Sig.
Constant	0.23	0.62	0.37	
Long. acc. (max.)	-0.31	0.060	-5.17	***
Long. dec. (max.)	0.27	0.033	8.00	***
Lat. vel. (mean)	6.73	2.65	2.54	*
Lat. pos. (mean)	0.42	0.090	4.74	***
Warning (yes/no)	-0.30	0.14	-2.19	*
CE1, rural (yes/no)	0.95	0.40	2.41	*
	Random effects			
	$\sigma^2[e] =$		2.15 (87%)	
	$\sigma^2[u] =$		0.32 (13%)	
	Model fit			
	Observations: 533			
	R-Squared: 0.35			
	Adj. R-Squared: 0.34			
Hausman test			*0.172*	
Breusch-Pagan Lagrange Multiplier Test			*$\approx$ e-11*	

Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Table 6.8.: VRU panel model results (CE1 and CE2) using brake displacement (max.) as a dependent variable

Critical event 1				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.015	0.020	0.76	
Long. dec. (max.)	-0.14	0.0016	-91.49	***
Lat. dec. (mean.)	0.11	0.063	1.70	.
Long. vel. (mean)	-0.0037	0.0012	-3.16	**
Lat. vel. (mean)	-0.35	0.10	-3.39	***
Lat. pos. (mean)	-0.0099	0.0035	-2.83	**
Distraction (yes/no)	0.017	0.0068	2.48	*
Female (yes/no)	-0.015	0.0077	-1.95	.
	Random effects			
	$\sigma^2[e]$ =	0.0016 (86.2%)		
	$\sigma^2[u]$ =	0.00025 (13.8%)		
	Model fit			
	Observations: 178			
	R-Squared: 0.98			
	Adj. R-squared: 0.98			
Hausman test		*0.09*		
Breusch-Pagan Lagrange Multiplier Test		*0.007*		

Critical event 2				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.27	0.093	2.88	**
Long. vel. (max.)	0.011	0.0061	1.78	.
Perc. ease of use (i-DREAMS)	-0.066	0.027	-2.45	*
	Random effects			
	$\sigma^2[e]$ =	0.068 (78%)		
	$\sigma^2[u]$ =	0.019 (22%)		
	Model fit			
	Observations: 180			
	R-Squared: 0.052			
	Adj. R-squared: 0.041			
Hausman test test		*0.56*		
Breusch-Pagan Lagrange Multiplier Test		*0.007*		
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**				

Table 6.9.: VRU panel model results (CE3 and merged events) using brake displacement (max.) as a dependent variable

Critical event 3												
	No effects (OLS)				**fixed effects**				**Random effects**			
	β	SE	t-value	sig	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	0.14	0.049	2.86	**	-0.053	0.019	-2.83	**	0.14	0.049	2.83	**
Long. acc. (mean)	-0.039	0.012	-3.15	**	-0.14	0.0023	-61.27	***	-0.039	0.013	-3.14	**
Long. dec. (max.)	-0.15	0.0017	-83.85	***	-0.74	0.30	-2.46	*	-0.15	0.0017	-83.59	***
Lat. dec. (mean.)	-0.59	0.24	-2.45	*	-0.013	0.0030	-4.50	***	-0.60	0.24	-2.45	*
Long. vel. (mean)	-0.0077	0.0020	-3.81	***	-0.0036	0.0084	-0.43		-0.0078	0.0020	-3.84	***
Lat. pos. (mean)	-0.018	0.0067	-2.74	**					-0.018	0.0067	-2.68	**
									Random effects			
									$\sigma^2[e]$ =	3.04 e-04 (98.3%)		
									$\sigma^2[u]$ =	5.30 e-05 (1.7%)		
	Model fit				**Model fit**				**Model fit**			
	Observations: 177				Observations: 177				Observations: 177			
	R-Squared: 0.98				R-Squared: 0.97				R-Squared: 0.98			
	Adj. R-squared: 0.98				Adj. R-squared: 0.96				Adj. R-squared: 0.98			
Hausman test			*0.015*									
F test for individual effects			*0.21*									

Merged events								
	fixed effects				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant					0.095	0.022	4.35	***
Long. acc. (mean)	-0.015	0.0047	-3.26	***	-0.012	0.0044	-2.80	**
Long. dec. (max.)	-0.14	0.0011	-127.93	***	-0.14	0.0010	-141.75	***
Long. vel. (mean)	-0.0080	0.00092	-8.66	***	-0.0063	8.12 e-04	-7.79	***
Lat. vel. (mean)	-0.14	0.090	-1.56		-0.18	0.089	-1.97	*
Lat. pos. (mean)	-0.010	0.0030	-3.31	***	-0.013	0.0030	-4.25	***
CE1, rural (yes/no)	-0.020	0.014	-1.44		-0.038	0.014	-2.80	**
					Random effects			
					$\sigma^2[e]$ =	0.0024 (92.4%)		
					$\sigma^2[u]$ =	0.00020 (7.6%)		
	Model fit				**Model fit**			
	Observations: 533				Observations: 533			
	R-Squared: 0.97				R-Squared: 0.98			
	Adj. R-squared: 0.97				Adj. R-squared: 0.98			
Hausman test			*≈ e-6*					
F test for individual effects			*≈ e-6*					
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**								

Table 6.10.: VRU panel model results (CE1 and CE2) using gas pedal displacement (SD) as a dependent variable

Critical event 1				
	Random effects			
	β	SE	t-value	Sig.
Constant	-0.0029	0.020	-0.15	
Long. acc. (mean)	0.086	0.0052	16.48	***
Long. dec. (mean)	-0.027	0.0038	-7.26	***
Long. vel. (max.)	0.0068	0.0010	6.91	***
	Random effects			
	$\sigma^2[e]$ =	0.0016 (68.1%)		
	$\sigma^2[u]$ =	0.00074 (31.9%)		
	Model fit			
	Observations: 178			
	R-Squared: 0.75			
	Adj. R-squared: 0.74			
Hausman test			*0.32*	
Breusch-Pagan Lagrange Multiplier Test			$\approx$ *e-4*	

Critical event 2				
	Random effects			
	β	SE	t-value	Sig.
Constant	-0.012	0.043	-0.28	
Long. acc. (max.)	0.11	0.0072	15.33	***
Long. dec. (max.)	-0.0044	0.0016	-2.71	**
Long. vel. (max.)	0.0046	0.0011	4.024	***
Lat. acc. (mean)	-0.31	0.18	-1.69	.
Lat. pos. (mean)	0.011	0.0063	1.74	.
	Random effects			
	$\sigma^2[e]$ =	0.0014 (83.4%)		
	$\sigma^2[u]$ =	0.00028 (16.6%)		
	Model fit			
	Observations: 178			
	R-Squared: 0.68			
	Adj. R-squared: 0.67			
Hausman test			*0.113*	
Breusch-Pagan Lagrange Multiplier Test			*0.05*	
Sig. codes: 0 ′*′ 0.001 ′**′ 0.01 ′*′ 0.05 ′.′ 0.1 ′ ′ 1**				

Table 6.11.: VRU panel model results (CE3 and merged events) using gas pedal displacement (SD) as a dependent variable

Critical event 3												
	No effects (OLS)				**fixed effects**				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-0.0026	0.021	-0.124		-0.14	0.0024	-60.84	***	0.091	0.027	3.39	***
Long. acc. (max.)	-0.14	0.0017	-85.67	***	-0.0091	0.0026	-3.53	***	-0.011	0.0020	-5.24	***
Long. vel. (mean)	-0.0052	0.0016	-3.207	**					0.0040	0.0021	1.94	.
Female (yes/no)	-0.017	0.0091	-1.904	.					0.024	0.014	1.68	.
									Random effects			
									$\sigma^2[e]$ =	0.0035 (68.6%)		
									$\sigma^2[u]$ =	0.0016 (31.4%)		
	Model fit				**Model fit**				**Model fit**			
	Observations: 178				Observations: 178				Observations: 178			
	R-Squared: 0.98				R-Squared: 0.97				R-Squared: 0.16			
	Adj. R-squared: 0.98				Adj. R-squared: 0.95				Adj. R-squared: 0.15			
Hausman test			*≈ e-16*									
F test for individual effects			*0.17*									

Merged events				
	Random effects			
	β	SE	t-value	Sig.
Constant	-0.040	0.011	-3.79	***
Long. acc. (max.)	0.036	0.0018	20.30	***
Long. dec. (mean)	-0.015	0.0031	-4.85	***
Long. vel. (max.)	0.0100	0.00066	15.29	***
Lat. pos. (SD)	-0.0270	0.0062	-4.35	***
Distraction (yes/no)	-0.0110	0.0043	-2.64	**
CE2, urban (yes/no)	0.0160	0.0045	3.67	***
	Random effects			
	$\sigma^2[e]$ =	0.0020 (89%)		
	$\sigma^2[u]$ =	0.00024 (11%)		
	Model fit			
	Observations: 533			
	R-Squared: 0.71			
	Adj. R-Squared: 0.70			
Hausman test			*0.26*	
Breusch-Pagan Lagrange Multiplier Test			*≈ e-10*	
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**				

Table 6.12.: VRU panel model results using longitudinal acceleration [Abs.(max.)] as a dependent variable

Critical event 1				
	Random effects			
	β	SE	t-value	Sig.
Constant	-1.77	1.36	-1.31	
Long. vel. (max.)	-0.15	0.060	-2.50	*
Lat. pos. (mean)	0.47	0.23	2.07	*
Perceived usefulness (ADAS)	-0.55	0.30	-1.84	.
	Random effects			
	$\sigma^2[e]$ = 9.21 (83.5%)			
	$\sigma^2[u]$ = 1.81 (16.5%)			
	Model fit			
	Observations: 180			
	R-Squared: 0.085			
	Adj. R-squared : 0.069			
Hausman test			*0.15*	
Breusch-Pagan Lagrange Multiplier Test			*0.038*	

Critical event 2				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.83	1.14	0.73	
Long. vel. (max.)	-0.18	0.075	-2.44	*
Perc. ease of use (ADAS)	0.75	0.33	2.26	*
	Random effects			
	$\sigma^2[e]$ = 8.00 (77%)			
	$\sigma^2[u]$ = 2.38 (23%)			
	Model fit			
	Observations: 180			
	R-Squared: 0.16			
	Adj. R-squared: 0.15			
Hausman test			*0.92*	
Breusch-Pagan Lagrange Multiplier Test			*0.0074*	

Critical event 3				
	Random effects			
	β	SE	t-value	Sig.
Constant	-0.47	1.17	-0.40	
Long. vel. (max.)	-0.19	0.073	-2.53	*
Steer. wheel angle (SD)	-0.57	0.20	-2.87	**
Warning (yes/no)	1.41	0.53	2.69	**
Female (yes/no)	1.17	0.63	1.87	.
	Random effects			
	$\sigma^2[e]$ = 10.24 (78.4%)			
	$\sigma^2[u]$ = 2.81 (21.6%)			
	Model fit			
	Observations: 178			
	R-Squared: 0.060			
	Adj. R-squared: 0.049			
Hausman test			*0.9*	
Breusch-Pagan Lagrange Multiplier Test			*0.026*	

Merged events				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.065	0.68	0.095	
Long. vel. (max.)	-0.18	0.036	-5.04	***
Perceived ease of use (i-DREAMS)	0.51	0.23	2.27	*
CE2, urban (yes/no)	0.78	0.32	2.40	*
	Random effects			
	$\sigma^2[e]$ = 10.99 (86.6%)			
	$\sigma^2[u]$ = 1.70 (13.4%)			
	Model fit			
	Observations: 538			
	R-Squared: 0.089			
	Adj. R-Squared: 0.084			
Hausman test			*0.905*	
Breusch-Pagan Lagrange Multiplier Test			*≈ e-9*	

Sig. codes: 0 ’*’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1**

6.2.2. Tailgating models

In the below sub–section, model results and preliminary interpretation for the tailgating events are given, with the following selected dependent variables: log(Headway$_{min}$), log(TTC$_{min}$), maximum brake pedal displacement percentage (maximum), gas pedal displacement percentage variability, absolute value of maximum longitudinal acceleration.

1. Headway$_{min}$
   As Headway$_{min}$ for tailgating events was rather unbalanced, the logarithmic value of this variable was instead used; see a distribution of this variable [both Headway$_{min}$ and log(Headway$_{min}$] in Appendix D.2.3[2]. Results for these models are given in Table 6.13. Model results for CE1 revealed that the no–effects model performed better than the random–effects model (for which 7% of effects were individual). Significant variables were longitudinal control variables: acceleration (mean), and deceleration (max.). Also, lateral control variables: deceleration (mean), lateral position (mean) were found to be significant variables. Among conditions variables, distraction was found to negatively impact Headway$_{min}$, meaning being distracted while driving (as compared to not) would likely decrease the minimum time headway, or in other words, deteriorate driving performance. Finally, perceived usefulness of the system was also found to be highly significant for the dependent variable.

   For CE2, the no–effects model was also found to be better than the random effects one, with significant obtained variables for longitudinal control such as velocity (mean) and lateral control like acceleration (mean), velocity (mean), and lateral position (mean). For this case, the random–effects model had no effects coming from individual ones, which means the random–effects model was exactly the same as an ordinary least squared or no–effects model. For the CE3 model, the no–effects model was found to be the best, followed by the fixed–effects model, then the random–effects model (for which no random effects were found to be based on individual ones, meaning it is the same as the no–effects model). Significant obtained variables were longitudinal deceleration (max.), lateral acceleration (mean), lateral deceleration (max.), and lateral position (mean). Moreover, the road ahead fixation count was found to positively impact Headway$_{min}$ (the higher the road fixation, the higher the time headway to the vehicle ahead). Similarly, age was also found to have that same impact, meaning older drivers were more likely to keep a longer distance or time headway to the vehicle ahead, as compared to their younger counterparts.

   For the merged effects model, the random–effects model was found to be the better model. Significant variables obtained for longitudinal control were deceleration (max.), and velocity (max.); higher deceleration meant a possibly higher Headway$_{min}$, and a higher velocity meant a lower Headway$_{min}$, both of which make sense. Moreover, conditions like the presence of interventions or distraction negatively impacted Headway$_{min}$; in other words a higher distraction meant a lower Headway$_{min}$ (could mean a worse

[2]For the remainder of this section, and for the sake of simplicity, Headway$_{min}$ will be used to refer to log(Headway$_{min}$), and mostly as an impact on one is likely to impact the other directly.

driving performance), and driving with interventions in general would also mean a lower Headway_{min} (could be attributed to the fact that drivers rely more on interventions and therefore optimize their Headway_{min} due to the driving assistance). Finally, in the rural environment, as compared to other environments (urban and highway), the time to headway was likely to be lower.

2. $\log(\text{TTC}_{min})$:
   Similarly to the VRU events, TTC_{min} for tailgating events was rather unbalanced, the logarithmic value of this variable was instead used; see a distribution of this variable [both TTC_{min} and $\log(\text{TTC}_{min}$] in Appendix D.2.3[3]. Results of models for CE1 and CE2 are given in Table 6.14 and those of CE3 and the merged events dataset are given in Table 6.15. For each of CE1 and CE2, the random–effects models were found to be best. For CE1 for instance, this was also reflected in the higher R–squared value. Obtained significant variables were longitudinal acceleration (mean), longitudinal velocity (mean), lateral acceleration (max.), lateral deceleration (mean), and lateral position (mean). Moreover, perceived ease of use of the system was found to be highly significant for the minimum time–to–collision. For CE2, the maximum longitudinal velocity was the highly significant variable.
   For CE3, the fixed–effect models was found to be better than the random effect models (which was the same as no–effects model as there were no individual random effects). Obtained significant variables were longitudinal velocity (mean), deceleration (max.), and lateral position. Moreover, eye tracking metrics like fixation for road ahead led to a higher TTC_{min}; this makes sense as the more drivers fixate on the road, the more they pay attention, and therefore the more conservative is their driving likely to be, or the higher the distance kept to the vehicle ahead. Finally, the presence of warnings or intervention–systems led in general to lower TTC_{min}, which can be understood as way to compensate for risk, by relying on the warning–monitoring system, or could on the contrary be perceived as a distracting element.

   For the merged effects model, the fixed–effect model was also found to be the best. Obtained significant variables were longitudinal acceleration (mean, max), lateral position (SD), road fixation count, presence of warnings, or of a rural environment. For merged events with more observations, again the random effect model was found to be best. Longitudinal control parameters were found to be significant (mean and max. velocity), or lateral control ones including acceleration, deceleration, lateral position. Moreover, eye tracking metrics like gaze fixation count (road ahead), attitudinal variables like perceived ease of use of the system, or specific conditions for the experiment (warning presence) or road environment (rural) were all found to be highly influential on TTC_{min}.

3. Brake pedal percentage displaced (max.):
   Results are presented in Table 6.16. For the CE1 model, the OLS model was found to be better than the random model (3% individual effects) with variables such as

[3] For the remainder of this section, and for the sake of simplicity, TTC_{min} will be used instead of $\log(\text{TTC}_{min})$, as an impact on one is likely to impact the other directly.

lateral deceleration (max.), lateral velocity (mean), steering wheel angle (SD) being highly significant, as well as longitudinal control variables such as acceleration (max.), deceleration (max.) and steering wheel angle (mean). Moreover, distraction had a positive impact on the maximum brake percentage displaced (could mean that this was a compensatory effect due to distraction).

For the CE2 model, the random effect models was equivalent to the no–effect one (0% random indiviudal effects) with significant variables of longitudinal control such as longtiduinal acceleration (max.) and velocity (mean), and lateral control (lateral position variation). Moreover demographics such as attitudinal variables and gender were found to be highly influential on the maximum brake displacement; the system's perceived usefulness had a positive impact on the maximum brake percentage displaced, and females were more likely, as compared to males to have a higher maximum brake displacement.

For the CE3 model, the no–effects model was the best (the random–effects model resulted in only 2% of effects being due to individual ones, which meant that both the random and no effects model were quite similar). Longitudinal acceleration (mean), deceleration (max.), velocity (mean), lateral deceleration (mean) and velocity (mean) were all found to be highly significant.

Finally, for the merged effects model, the random–effects model (with 4% individual effects) was found to be the best one, with obtained significant variables being longitudinal deceleration (max.) and velocity (mean), but also the attitudinal variable perceived ease of use of the system (resulting from the factor analysis conducted in the previous analysis steps).

4. Gas pedal percentage displaced (SD):
   Results of CE1 and CE2 are given in Table 6.17. Results of CE3 and the merged events dataset are given in Table 6.18.

   For the CE1 model, the no–effects model was found to be better than the random effects one (10% due to individual effects), although both led to similar results; significant obtained variables were longitudinal acceleration (max.), deceleration (mean), velocity (max.).

   For the CE2 model, the fixed–effects model was better than the random effects one, and longitudinal acceleration, velocity, and deceleration, as well as lateral position, were all found to be highly significant. In addition, in the random–effects model, the perceived usefulness of ADAS and of the system tested were found to be highly significant, and likely to impact the gas pedal percentage variation.

   For the CE3, the no–effects model was found to be better than the random. Insights revealed that longitudinal velocity, acceleration, and deceleration (max.) were highly significant.

   The merged events model found the random–effects model to be best. Obtained significant variables were longitudinal velocity and acceleration (max.) and deceleration (max.). Moreover, the highway environment (or CE2) was found to lead to a lower deviation in the gas pedal displacement (in comparison with other road environments).

Overall, highway environment, longitudinal control (maximum velocity, maximum acceleration, deceleration), lateral control, and attitudinal variables (perceived usefulness) were all highlighted as meaningful variables in understanding the gas pedal displacement variability.

5. Longitudinal acceleration [Abs(max.)]:
   Results of CE1 and CE2 models are given in Table 6.19 and those of CE3 and the merged events models are given in Table 6.20.

   The CE1 model showed that the no–effects model is better than the random–effects model, for which 9% of effects noted were individual. Significant variables noted were lateral position (mean), but also the presence of distraction. For CE2, the no–effects model was also found to be better than the random effects one, with significant variables noted being longitudinal velocity, lateral position (SD), but also eye tracking metrics such as the dashboard fixation count. For the CE3 model, the no–effects model was found to be the best. In this model, the longitudinal velocity (mean) and lateral position (mean) were found to be highly significant. Finally, the merged effects model showed that the random–effects model was the best (with 10% of effects being individual). Lateral position (SD), longitudinal velocity (max.) were highly significant. Overall, longitudinal velocity, lateral position (SD or mean) were found to be highly significant for harsh acceleration (max absolute value); occasionally, distraction had a high impact as well, in addition to some fixation metrics. Also, the OLS was mostly better than the random, but in the merged model, the random–effects model was found to be best.

Table 6.13.: Tailgating panel model results using log($Headway_{min}$) as a dependent variable

Critical event 1

	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	7.15	0.99	7.23	***	7.23	0.99	7.28	***
Long. acc. (mean)	-0.77	0.22	-3.54	***	-0.78	0.22	-3.52	***
Long. dec. (max.)	0.18	0.061	2.87	**	0.18	0.061	2.89	**
Lat. dec. (mean)	-4.55	1.45	-3.14	**	-4.25	1.52	-2.80	**
Lat. pos. (mean)	-0.72	0.14	-5.28	***	-0.73	0.14	-5.32	***
Distraction (yes/no)	-0.49	0.19	-2.64	**	-0.49	0.18	-2.68	**
PU (i-DREAMS)	0.21	0.091	2.27	*	0.21	0.10	2.18	*
					Random effects			
					$\sigma^2[e]$ =	1.08 (93.1%)		
					$\sigma^2[u]$ =	0.08 (6.9%)		
	Model fit				**Model fit**			
	Observations: 176				Observations: 176			
	R-Squared: 0.34				R-Squared: 0.36			
	Adj. R-squared: 0.34				Adj. R-squared: 0.34			
Hausman test			*0.21*					
Langrange Multiplier Test- Breusch Pagan			*0.55*					

Critical event 2

	Random effects			
	β	SE	t-value	Sig.
Constant	6.34	0.54	11.76	***
Lat. acc. (mean)	-3.71	1.20	-3.10	**
Long. vel. (mean)	-0.088	0.013	-7.02	***
Lat. vel. (mean)	6.50	1.45	4.49	***
Lat. pos. (mean)	-0.24	0.045	-5.30	***
	Random effects			
	$\sigma^2[e]$ =	1 (100%)		
	$\sigma^2[u]$ =	0 (0%)		
	Model fit			
	Observations: 180			
	R-Squared: 0.50			
	Adj. R-squared: 0.49			
Hausman test			*0.624*	
Breusch-Pagan Lagrange Multiplier Test			*0.78*	

Critical event 3

	fixed effects				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant					0.49	0.35	1.40	
Long. dec. (max.)	0.20	0.067	2.96	**	0.24	0.050	4.81	***
Lat. acc. (mean)	13.81	7.09	1.95	.	8.19	4.76	1.72	.
Lat. dec. (max.)	0.48	0.66	0.73		1.51	0.54	2.79	**
Lat. pos. (mean)	0.20	0.086	2.30	*	0.25	0.072	3.46	***
Road ahead fix. count	0.0088	0.0027	3.21	**	0.0085	0.0021	4.06	***
Age					0.024	0.0082	2.92	**
					Random effects			
					$\sigma^2[e]$ =	0.8882 (100%)		
					$\sigma^2[u]$ =	0 (0%)		
	Model fit				**Model fit**			
	Observations: 175				Observations: 175			
	R-Squared: 0.21				R-Squared: 0.32			
	Adj. R-squared: -0.26				Adj. R-squared: 0.29			
Hausman test			*0.010*					
F test for individual effects			*0.29*					

Merged events

	Random effects			
	β	SE	t-value	Sig.
Constant	3.41	0.17	19.53	***
Long. dec. (max.)	0.20	0.035	5.67	***
Long. vel. (max.)	-0.052	0.0066	-7.83	***
Distraction (yes/no)	-0.24	0.12	-2.03	*
Warning (yes/no)	-0.44	0.12	-3.63	***
CE1, rural (yes/no)	-0.46	0.10	-4.42	***
	Random effects			
	$\sigma^2[e]$ =	1.26 (91.6%)		
	$\sigma^2[u]$ =	0.12 (8.4%)		
	Model fit			
	Observations: 525			
	R-Squared: 0.25			
	Adj. R-Squared: 0.25			
Hausman test			*0.06*	
Breusch-Pagan Lagrange Multiplier Test			*≈ e-5*	

Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Table 6.14.: Tailgating panel model results (CE1 and CE2) using log(TTC$_{min}$) as a dependent variable

Critical event 1								
	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	8.91	0.84	10.61	***	9.11	0.80	11.34	***
Long. acc. (mean)	-0.58	0.16	-3.62	***	-0.58	0.16	-3.76	***
Long. dec. (max.)	0.26	0.047	5.65	***	0.25	0.046	5.46	***
Lat. acc. (max.)	-0.72	0.30	-2.43	*	-0.79	0.26	-3.04	**
Lat. dec. (mean)	-5.86	1.80	-3.26	**	-6.20	1.82	-3.42	***
Long. vel. (mean)	-0.068	0.027	-2.48	*	-0.060	0.028	-2.17	*
Lat. pos. (mean)	-0.64	0.10	-6.41	***	-0.69	0.097	-7.10	***
Perc. ease of use (i-DREAMS)	-0.14	0.065	-2.18	*	-0.15	0.083	-1.83	.
					Random effects			
					$\sigma^2[e]$ =	0.45 (68.3%)		
					$\sigma^2[u]$ =	0.21 (31.7%)		
	Model fit				**Model fit**			
	Observations: 170				Observations: 170			
	R-Squared: 0.49				R-Squared: 0.51			
	Adj. R-squared: 0.47				Adj. R-squared: 0.49			
Hausman test			*0.39*					
Breusch-Pagan Lagrange Multiplier Test			*0.0087*					
Sig. codes: 0 ′*′ 0.001 ′**′ 0.01 ′*′ 0.05 ′.′ 0.1 ′ ′ 1**								

Critical event 2				
	Random effects			
	β	SE	z-value	Sig.
Constant	4.11	0.33	12.48	***
Long. vel. (max.)	-0.058	0.011	-5.29	***
	Random effects			
	$\sigma^2[e]$ =	0.84 (76.7%)		
	$\sigma^2[u]$ =	0.26 (23.3%)		
	Model fit			
	Observations: 172			
	R-Squared: 0.15			
	Adj. R-Squared: 0.15			
Hausman test			*0.31*	
Breusch-Pagan Lagrange Multiplier Test			*0.013*	
Sig. codes: 0 ′*′ 0.001 ′**′ 0.01 ′*′ 0.05 ′.′ 0.1 ′ ′ 1**				

Table 6.15.: Tailgating panel model results (CE3 and merged events) using log(TTC_{min}) as a dependent variable

Critical event 3								
	fixed effects				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant					4.02	0.38	10.62	***
Long. vel. (mean)	-0.12	0.042	-2.83	**	-0.15	0.034	-4.53	***
Long. dec. (max.)	0.28	0.052	5.44	***	0.29	0.040	7.20	***
Lat. pos. (mean)	0.40	0.092	4.38	***	0.41	0.076	5.47	***
Road ahead fix. count	0.0045	0.0024	1.87	.	0.0070	0.0018	3.86	***
Warning (yes/no)	-0.49	0.14	-3.51	***	-0.37	0.13	-2.84	**
					Random effects			
					$\sigma^2[e]$ =	0.0023 (100%)		
					$\sigma^2[u]$ =	0 (0%)		
	Model fit				**Model fit**			
	Observations: 171				Observations: 171			
	R-Squared: 0.44				R-Squared: 0.43			
	Adj. R-squared: 0.10				Adj. R-squared: 0.41			
Hausman test			*0.0051*					
F test for individual effects			*0.0068*					

Merged events								
	fixed effects				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant					3.28	0.15	22.62	***
Long. acc. (mean)	-0.31	0.10	-3.18	**	-0.29	0.093	-3.15	**
Long. dec. (max.)	0.28	0.031	8.98	***	0.26	0.029	9.08	***
Lat. pos. (SD)	0.41	0.12	3.55	***	0.43	0.11	3.86	***
Road ahead fix. count	0.0042	0.0016	2.56	*	0.0049	0.0015	3.28	**
Warning (yes/no)	-0.33	0.085	-3.87	***	-0.30	0.084	-3.63	***
CE1, rural (yes/no)	-0.17	0.079	-2.17	*	-0.17	0.079	-2.11	*
					Random effects			
					$\sigma^2[e]$ =	0.66 (87.3%)		
					$\sigma^2[u]$ =	0.096 (12.7%)		
	Model fit				**Model fit**			
	Observations: 484				Observations: 484			
	R-Squared: 0.31				R-Squared: 0.30			
	Adj. R-Squared: 0.20				Adj. R-Squared: 0.29			
Hausman test			*0.00090*					
Breusch-Pagan Lagrange Multiplier Test			$\approx$ *e-6*					
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**								

Table 6.16.: Tailgating panel model results using the brake percentage displacement (max.) as a dependent variable

Critical event 1								
	No effects (OLS)				Random effects			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-0.11	0.0087	-13.02	***	-0.11	0.0088	-12.92	***
Long. acc. (max.)	-0.0082	0.0045	-1.82	.	-0.0079	0.0045	-1.76	.
Long. dec. (max.)	-0.15	0.0029	-51.96	***	-0.15	0.0029	-51.80	***
Lat. dec. (max.)	0.14	0.034	4.27	***	0.14	0.034	4.19	***
Lat. vel. (mean)	0.66	0.23	2.91	**	0.66	0.23	2.90	**
Steer. wheel angle (mean)	-0.073	0.036	-2.05	*	-0.071	0.036	-2.00	*
Steer. wheel angle (SD)	0.017	0.0058	2.95	**	0.017	0.0059	2.87	**
Distraction (yes/no)	0.023	0.0091	2.50	*	0.023	0.0090	2.52	*
					Random effects			
					$\sigma^2[e] =$	2.58e-03 (96.8%)		
					$\sigma^2[u] =$	8.53e-05 (3.2%)		
	Model fit				**Model fit**			
	Observations: 176				Observations: 176			
	R-Squared: 0.96				R-Squared: 0.96			
	Adj. R-squared: 0.96				Adj. R-squared: 0.96			
Hausman test			*0.79*					
Breusch-Pagan Lagrange Multiplier Test			*0.43*					

Critical event 2				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.17	0.030	5.46	***
Long. acc. (max.)	-0.025	0.0035	-7.30	***
Long. vel. (mean)	-0.0037	0.0012	-3.06	**
Lat. pos. (SD)	0.065	0.019	3.42	***
Perc. usefulness (i-DREAMS)	0.014	0.0085	1.65	.
Female (yes/no)	0.028	0.017	1.70	.
	Random effects			
	$\sigma^2[e] =$	0.012 (100%)		
	$\sigma^2[u] =$	0 (0%)		
	Model fit			
	Observations: 180			
	R-Squared: 0.32			
	Adj. R-squared: 0.30			
Hausman test			*0.7*	
Langrange Multiplier Test- Breusch Pagan			*0.06*	

Critical event 3								
	No effects (OLS)				Random effects			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	0.040	0.019	2.11	*	0.040	0.019	2.11	*
Long. acc. (mean)	-0.023	0.0094	-2.42	*	-0.023	0.0094	-2.41	*
Long. dec. (max.)	-0.15	0.0025	-59.15	***	-0.15	0.0025	-59.12	***
Long. vel. (mean)	-0.010	0.0016	-6.24	***	-0.010	0.0016	-6.25	***
Lat. dec. (mean)	-0.39	0.17	-2.22	*	-0.39	0.18	-2.20	*
Lat. vel. (mean)	-0.78	0.34	-2.30	*	-0.77	0.34	-2.28	*
					Random effects			
					$\sigma^2[e] =$	2.26e-03 (98.2%)		
					$\sigma^2[u] =$	4.22e-05 (1.8%)		
	Model fit				**Model fit**			
	Observations: 175				Observations: 175			
	R-Squared: 0.96				R-Squared: 0.96			
	Adj. R-squared: 0.96				Adj. R-squared: 0.96			
Hausman test			*0.96*					
Breusch-Pagan Lagrange Multiplier Test			*0.49*					

Merged events				
	Random effects			
	β	SE	t-value	Sig.
Constant	-0.00023	0.0092	-0.025	
Long. dec. (max.)	-0.14	0.0020	-68.65	***
Long. vel. (mean)	-0.0060	0.00045	-13.33	***
Perc. ease of use (i-DREAMS)	0.0074	0.0035	2.11	*
	Random effects			
	$\sigma^2[e] =$	0.0044 (95.8%)		
	$\sigma^2[u] =$	0.00019 (4.2%)		
	Model fit			
	Observations: 525			
	R-Squared: 0.91			
	Adj. R-Squared: 0.90			
Hausman test			*0.36*	
Breusch-Pagan Lagrange Multiplier Test			*0.04*	

Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Table 6.17.: Tailgating panel model results (CE1 and CE2) using gas pedal displacement (SD) as a dependent variable

Critical event 1								
	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-0.036	0.013	-2.77	**	-0.035	0.014	-2.61	**
Long. acc. (max.)	0.041	0.0033	12.51	***	0.041	0.0033	12.59	***
Long. dec. (mean)	-0.054	0.010	-5.22	***	-0.053	0.010	-5.09	***
Long. vel. (max.)	0.0075	0.00076	9.90	***	0.0075	0.00078	9.56	***
					Random effects			
					$\sigma^2[e] =$	0.0013 (89.2%)		
					$\sigma^2[u] =$	0.00016 (10.8%)		
	Model fit				**Model fit**			
	Observations: 178				Observations: 178			
	R-Squared: 0.82				R-Squared: 0.82			
	Adj. R-squared: 0.82				Adj. R-squared: 0.81			
Hausman test			*0.89*					
Breusch-Pagan Lagrange Multiplier Test			*0.118*					

Critical event 2								
	fixed effects				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant					-0.0082	0.029	-0.28	
Long. vel. (max.)	0.0029	0.0012	2.37	*	0.0047	0.00092	5.12	***
Long. acc. (max.)	0.054	0.0079	6.87	***	0.049	0.0064	7.69	***
Long. dec. (max.)	-0.037	0.0072	-5.11	***	-0.034	0.0058	-5.87	***
Lat. pos. (SD)	-0.043	0.015	-2.79	**	-0.046	0.013	-3.41	***
PU (ADAS)					0.021	0.0076	2.72	**
PU (i-DREAMS)					-0.018	0.0076	-2.35	*
					Random effects			
					$\sigma^2[e] =$	0.0051 (84.6%)		
					$\sigma^2[u] =$	0.00093 (15.4%)		
	Model fit				**Model fit**			
	Observations: 170				Observations: 170			
	R-Squared: 0.51				R-Squared: 0.51			
	Adj. R-squared: 0.21				Adj. R-squared: 0.49			
Hausman test			*0.035*					
F test for individual effects			*0.026*					
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**								

Table 6.18.: Tailgating panel model results (CE3 and merged events) using gas pedal displacement (SD) as a dependent variable

Critical event 3								
	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-0.0043	0.014	-0.32		-0.000012	0.014	-0.0008	
Long. vel. (max.)	0.0067	0.0010	6.83	***	0.0064	0.0010	6.53	***
Long. acc. (max.)	0.042	0.0032	13.17	***	0.041	0.0032	12.71	***
Long. dec. (max.)	-0.0069	0.0023	-3.01	**	-0.0069	0.0023	-3.03	**
					Random effects			
					$\sigma^2[e]$ =	0.0017 (91.4%)		
					$\sigma^2[u]$ =	0.00016 (8.6%)		
	Model fit				**Model fit**			
	Observations: 175				Observations: 175			
	R-Squared: 0.70				R-Squared: 0.68			
	Adj. R-squared: 0.70				Adj. R-squared: 0.68			
Hausman test			*0.07*					
Breusch-Pagan Lagrange Multiplier Test			*0.193*					

Merged events				
	Random effects			
	β	SE	t-value	Sig.
Constant	0.014	0.0082	1.77	.
Long. vel. (max.)	0.0054	0.00044	12.28	***
Long. acc. (mean)	0.12	0.0056	21.69	***
Long. dec. (max.)	-0.0084	0.0018	-4.78	***
CE2, highway (yes/no)	-0.016	0.0072	-2.21	*
	Random effects			
	$\sigma^2[e]$ =	0.0027 (94.1%)		
	$\sigma^2[u]$ =	0.00017 (5.9%)		
	Model fit			
	Observations: 523			
	R-Squared: 0.69			
	Adj. R-Squared: 0.69			
Hausman test			*0.84*	
Breusch-Pagan Lagrange Multiplier Test			*0.015*	
sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**				

Table 6.19.: Tailgating panel model results (CE1 and CE2) using longitudinal acceleration [Abs. (max.)] as a dependent variable

Critical event 1								
	No effects (OLS)				Random effects			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-5.30	2.15	-2.47	*	-5.18	2.15	-2.41	*
Lat. pos. (mean)	0.66	0.30	2.19	*	0.64	0.30	2.13	*
Distraction (yes/no)	0.83	0.46	1.81	.	0.84	0.44	1.91	.
					Random effects			
					$\sigma^2[e]$ =	7.67 (90.6%)		
					$\sigma^2[u]$ =	0.80 (9.4%)		
	Model fit				**Model fit**			
	Observations: 179				Observations: 179			
	R-Squared: 0.045				R-Squared: 0.045			
	Adj. R-squared: 0.034				Adj. R-squared: 0.035			
Hausman test			*0.393*					
Breusch-Pagan Lagrange Multiplier Test			*0.114*					

Critical event 2								
	No effects (OLS)				Random effects			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	2.80	0.66	4.26	***	2.74	0.67	4.08	***
Long. vel. (mean)	-0.12	0.025	-4.76	***	-0.12	0.025	-4.56	***
Lat. pos. (SD)	-0.87	0.40	-2.17	*	-0.89	0.40	-2.22	*
Dashboard fix. count	0.053	0.029	1.82	.	0.053	0.029	1.81	.
					Random effects			
					$\sigma^2[e]$ =	5.17 (91.8%)		
					$\sigma^2[u]$ =	0.46 (8.2%)		
	Model fit				**Model fit**			
	Observations: 180				Observations: 180			
	R-Squared: 0.17				R-Squared: 0.16			
	Adj. R-squared: 0.16				Adj. R-squared:0.15			
Hausman test			*0.82*					
Breusch-Pagan Lagrange Multiplier Test			*0.183*					

Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Table 6.20.: Tailgating panel model results (CE3 and merged events) using longitudinal acceleration [Abs. (max.)] as a dependent variable

Critical event 3								
	No effects (OLS)				**Random effects**			
	β	SE	t-value	Sig.	β	SE	t-value	Sig.
Constant	-0.44	1.13	-0.38		-0.72	1.13	-0.64	
Long. vel. (mean)	0.21	0.11	1.88	.	0.24	0.11	2.10	*
Lat. pos. (mean)	-0.93	0.25	-3.76	***	-0.93	0.25	-3.78	***
					Random effects			
					$\sigma^2[e] =$	8.27 (91.6%)		
					$\sigma^2[u] =$	0.76 (8.4%)		
	Model fit				**Model fit**			
	Observations: 175				Observations: 175			
	R-Squared: 0.076				R-Squared: 0.077			
	Adj. R-Squared: 0.065				Adj. R-Squared: 0.066			
Hausman test			*0.06*					
Breusch-Pagan Lagrange Multiplier Test			*0.23*					

Merged events				
	Random effects			
	β	SE	z-value	Sig.
Constant	2.35	0.48	4.88	***
Long. vel. (max.)	-0.13	0.027	-4.87	***
Lat. pos. (SD)	-1.05	0.33	-3.20	***
	Random effects			
	$\sigma^2[e] =$	7.12 (89.6%)		
	$\sigma^2[u] =$	0.82 (10.4%)		
	Model fit			
	Observations: 534			
	R-Squared: 0.066			
	Adj. R-Squared: 0.062			
Hausman test			*0.62*	
Breusch-Pagan Lagrange Multiplier Test			*$\approx$ e-6*	
Sig. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**				

7. Discussion and Conclusion

This final chapter presents the discussion of this work's results (Section 7.1), highlighting the main insights obtained on the presented technology's acceptance, on the findings from the panel regression models, but also discusses the transferability of some of the findings across different modes; the latter is openly available in Al Haddad, Abouelela, Graham Hancox, et al. (2022). Then, the chapter highlights the thesis highlight and contributions (Section 7.2), reflecting on the answered objectives (that were introduced in Section 1.3). Finally, Section 7.3 sheds light on the work's limitations, but then discusses future work opportunities based on the work presented in this dissertation.

7.1. Discussion

This section discusses the results based on the findings obtained in Sections 6.1 and 6.2, with an aim to answer many of the hypotheses and research questions laid out in this work. Finally, an analysis of transferability of findings is presented, based on a partial replicability of the models developed in Section 6.1, using a dataset of truck and tram simulator experiments; these have been collected within the same project case–study, following the same protocols given in Section 4.3.3, however not within the scope of this dissertation.

7.1.1. Technology acceptance

Findings for this analysis revealed that respondents overall had positive views of ADAS (Figure 5.6), meaning that they mostly thought it was useful (good idea, has benefits like maintaining driving safety), trusted it, but also found the information ADAS provided to be clear and understandable; in general, very few participants perceived ADAS as distracting. Similarly, for the i—DREAMS system (Figure 5.7), most participants seemed to find it useful (to maintain safe driving), indicating an overall high level of trust for the system, stating that they would keep using it and even recommend to others (most participants seemed to agree with this).

The i–DREAMS system was also found to be rather easy to use. Overall, the i–DREAMS' system clarity was also assessed (Figure 5.8) and was perceived to be quite high; this was also the case for visual clarity, but less so for sound clarity. These findings are consistent with the insights provided by the qualitative analysis. In particular, the latter revealed that some improvements can be done by bringing in voice assistance to the warning–system in case of an over–speeding, or in dangerous situations. Some participants found the auditory warnings to be too loud or even confusing and/ distracting. For visual clarity, the qualitative analysis indicated that mostly, warning pictograms were similar to existing ADAS; yet, some comments indicated a confusion with regards to the numbers indicated on the pictograms (such as the one in Figure 4.3-b), whether they referred to time, distance, and were therefore found to be confusing or even distracting. For each of the visual or auditory improvements highlighted, there was a bit of contrast noticed by participants, which suggest a potential lack of familiarity with the system, which could explain this discrepancy, as opposed to a high level of understanding of ADAS in general. One way to get around this would be to have a longer test phase in which participants get further acquainted with the system's different functionalities (with the disadvantage of course of possible higher biases and scenario predictability); better instructing participants on the meaning of such warnings would possibly allow them to better benefit from their usefulness, increasing thereby the system acceptability, as noted in Rossi, Gastaldi, Biondi, et al. (2020).

In assessing whether any of the participants' demographics had an impact on their perceptions and attitudes towards ADAS, the i–DREAMS system, or driving distraction, Chi–square tests were conducted with gender as the variable of interest. Results of these tests revealed that gender had no significant impacts on the observed attitudes. Further, the factor analysis models on perceptions towards ADAS and the i–DREAMS system led to extracting two main factors: perceived usefulness, and perceived ease of use; while the extracted factors are different than the ones identified in M. M. Rahman, Strawderman, et al. (2018), from which many survey items were extracted, this can be explained by the fact that not all survey items were used in the current study. Still, the obtained findings are in line with the main premises of the technology acceptance model, and compatible with the work of several researchers who used this method to understand users' perceptions of transportation systems (Tyrinopoulos and Antoniou, 2008; Efthymiou, Antoniou, and Waddell, 2013), or even acceptance of disruptive transport technologies (Al Haddad, Chaniotakis, et al., 2020), in which they reduced initial indicators to fewer factors, each explaining more than 10% of the total variance (with one exception at most), with a cumulative total variance ranging roughly from an average of 46% to 55%. Overall, the above–mentioned study design, analysis, and results have led to answering the research question on better understanding drivers' acceptance of the i–DREAMS warning system. People seemed to in general have had positive perceptions towards it, finding it useful, easy to use, and in particular clear (both auditorily, but even more visually).

To understand whether this acceptance could be represented by the classical TAM, the hypotheses drawn in Figure 3.1 were tested. To answer the first hypothesis, an ordered logit model was developed, with "i–DREAMS intention to use" as a dependent variable, and the factors resulting from the factor analysis (Table 6.3)– i–DREAMS usefulness and ease of use, as independent variables. The model results (Table 6.4) revealed that both perceived ease of use and usefulness positively and significantly impacted the intention to use, validating thereby the first hypothesis, which is in line with the study by M. M. Rahman, Lesch, et al. (2017), in which TAM was found to be suitable to explain the variability in the behavioral intention to use ADAS. This is also in line with previous research (Biassoni, Ruscio, and Ciceri, 2016; Cho et al., 2017; Viktorová and Šucha, 2018) that highlighted that perceived safety benefits highly impact the system acceptance.

To test the second hypothesis (impacts of PEU and of external variables on PU), an ordinal least square model (OLS) –results in Table 6.5 revealed that the i–DREAMS perceived usefulness was highly impacted by the perceived usefulness of ADAS; this is expected, and also validates the hypothesis partially. On the other hand, there was no indication that the i–DREAMS perceived usefulness highly depended on the i–DREAMS perceived ease of use, which also can be due to the fact that both were newly calculated factors based on the factor analysis results (Table 6.3). Finally, the third hypothesis was also validated (impact of external variables on PEU), based on the model results presented in Table 6.6, in which the duration for which a driver has had his or her license significantly impacts his or her perceived ease of use, which could be associated to driver age (the longer the license duration, the older the participant is, in principle), which is compatible with previous research by Xu, Ye, and C. Wang (2021), in which they indicated that driver age is among the influencing factors for ADAS acceptance; yet main factors such as gender did not prove to be highly impactful for perceived ease of use, which again is expected as the Chi–square test result for attitude statements could not prove gender to be significant for any of the tested perceptions.

Overall, the three hypotheses were validated (at least partially), helping to conclude that the warning–monitoring system in the case of the driving simulator (in our case: the i–DREAMS system) can be represented by means of a technology acceptance model. Based on the findings, and only based on the fully validated hypotheses (without the link between PEU and PU, that was not validated), a representation of the validated TAM for the current study was drawn, as shown in Figure 7.1.

7.1.2. Datasets integration

Descriptive and inferential statistics for the simulator and eye tracking data, along with the eye tracking dataset visualization (both part of Section 5.4) revealed initial insights on the impact of both the i-DREAMS system and distraction on driving performance. In particular, in the intervention drive, longitudinal control parameters were found to have significantly changed (due to the presence of warnings), along with a decrease in the minimum time-to-collision (for VRU events), and an increase in the gaze (fixation count and duration) on the road ahead (for tailgating events). Distraction was also found to significantly impact longitudinal and lateral control parameters; for the latter, the lateral position and steering wheel angle variability were found to significantly increase due to distraction, which can be interpreted as a compensatory action for the higher cognitive load experienced by participants due to distraction. This pattern was also observed in the higher variability of the gas pedal displacement and brake pedal (max.) displacement, as a result of distraction. Finally, fixation counts and duration on the road ahead, the dashboard, and the pedestrian area, all decreased in the distraction drive, as participants were occupied using the mobile phone handed to them (reading or replying). This was also reflected in Figures 5.3, 5.4, and 5.5, where participants' gaze distribution appears to be more divided in the distraction drive, as compared to the baseline (intervention) drive.

Comparing the events among themselves (Section 5.4) also revealed a significant change in

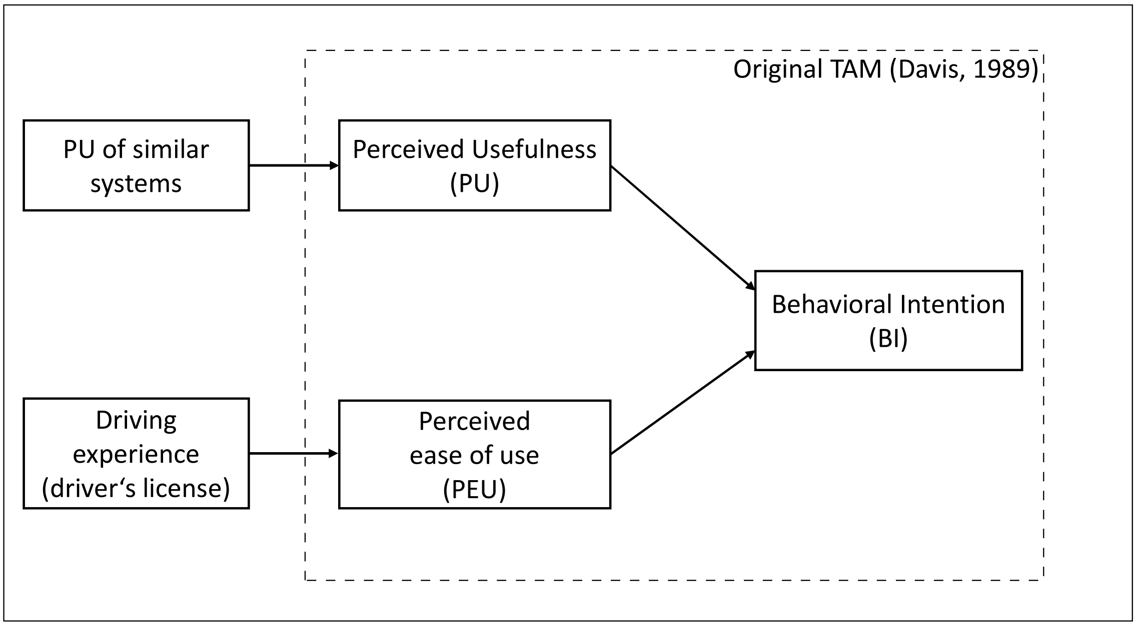


Figure 7.1.: Validated TAM based on the car driving simulator experiments *(own illustration)*

some of the parameters, based on the change in road environment. For the urban VRU events, as compared to the rural ones, a higher fixation on the road ahead and pedestrian areas was noticed; however, a lower one was noticed on the dashboard area. For tailgating events, the highway environment was reflected with a lower brake percentage, and a generally lower gaze intensity on the road ahead and on the dashboard area. For the urban tailgating events, a higher steering wheel variability and brake displacement was noticed, in addition to a higher gaze on the road ahead, as compared to the rural ones. By interpreting these findings, it becomes evident that there are significant differences due to distraction, to the presence of warnings, but also due to the environment type. Panel regression models can therefore come as a way to combine the different data sources, assuming that there are individual effects (pertaining to the participants) that need to be captured, and that these are random and non-negligible. As mentioned and summarized in Section 5.3.3, previous research categorized driving behavior parameters into different groups including longitudinal control, lateral control, risk perception parameters (including time-to-collision, gas and brake displacement factors). Finally, previous studies have shown proven the impact of socio-demographics and attitudes and perceptions on driving behavior. The developed panel regression models (in Section 6.2) combine these different data sources, with an attempt to answer or validate the different hypotheses drawn, for each of the VRU interactions (Section 6.2.1) and tailgating events (Section 6.2.2); these can be summarized as follows:

- Hypothesis 1: panel effects are random

- Hypothesis 2: individual effects are not null
- Hypothesis 3: prior attitudes and experiences significantly impact driving behavior
- Hypothesis 4: visual attention metrics are significant indicators for driving behavior
- Hypothesis 5: socio–demographics significantly impact driving behavior
- Hypothesis 6: longitudinal control factors are significant indicators for driving behavior
- Hypothesis 7: latitudinal control factors are significant indicators for driving behavior
- Hypothesis 8: the road environment significantly impacts driving behavior
- Hypothesis 9: the presence of warnings significantly impacts driving behavior
- Hypothesis 10: distraction significantly impacts driving behavior

The above hypotheses have been tested by means of the developed models, for the different datasets (using one specific event, or the merged dataset with all events) for each of the VRU and tailgating events models, where different driving performance variables were used as a dependent variable, and the different data source parameters as independent variables (including the eye tracking metrics, the questionnaire attitudes and perceptions, the demographics, the road environment and event types, but also the driving parameters as well). A summary of the hypotheses results is given in Table 7.1 and 7.2, for the VRU and tailgating events, respectively. It is important to note that for the sake of simplicity, a hypothesis validation refers to the failure of rejection of the opposite statement for one or more of the events used. For instance, Hypothesis 5 is validated by rejecting the statement "socio-demographics do not impact driving behavior"; therefore, it would be sufficient to develop models in which socio-demographics (such as age or gender) are highly significant (for instance to the 90% confidence level or above), in order to validate this hypothesis.

The hypotheses test results (for the VRU events models) revealed that all of the hypotheses have been validated in at least one more more model. In particular, panel effects were found to be mostly random, for which individual effects ranged from 8% to around 32% (except when those were found to be 0%, for which the random–effects model was nothing but a simple ordinary least squares, or a no–effects model). For attitudes and perceptions, those were reflected in the significant variables resulting from the previously developed factor analyses; these include the perceived usefulness for the i-DREAMS system, but also the perceived ease of use for ADAS and their perceived usefulness. For this hypothesis, it is important to note that the attitudes pertaining to the i-DREAMS system should be looked at carefully, as these stem from an analysis of respondents' perceptions of that system, which were collected after the second drive; in other words, for the first two drives, attitudinal constructs on the i-DREAMS system did not yet exist, as participants had not experienced it (and we had not yet collected their feedback) up until this point.

Visual attention or eye tracking metrics were found to be significant, as noted in the impact of the fixation count on the pedestrian areas; similarly, significant socio–demographics were extracted, including age and gender. Moreover, influential longitudinal control parameters included longitudinal acceleration (mean, max., and abs.[max.]), longitudinal deceleration (mean), longitudinal velocity (mean and max.). Similarly, lateral control parameters included lateral position (mean and SD), steering wheel angle (SD), lateral acceleration (mean), lateral deceleration (mean), and lateral velocity (mean). The road environment proved to also be influential including rural and urban environments. Finally, the conditions including the presence of warnings and distraction were also found to be significant; for the former, this was reflected in a lower TTC_{min}, and a higher maximum (absolute value) acceleration, which means in other words, more margin to drive closer to the "acceptable" limits or boundaries of safety (or perhaps a higher reliance on the system). For the latter, or for distraction, the same patterns were observed; this however could possibly be due to a compensatory effect of a deteriorating driving performance due to distraction. Drivers who are distracted possibly have a higher cognitive load (often demonstrated by the corresponding visual attention metrics), which means that to reach the same "safe" boundaries, they need to do more efforts to compensate for their poorer performance, so for example a higher braking pedal percentage could be one such example.

For the tailgating models (Table 7.2), most hypotheses were validated as well, for one or more of the datasets used. The best performing models mostly had random effects, with non–negligible individual effects (except for a few models, for which individual effects were null), ranging from about 2% to around 32% for the different models. Attitudinal factors that proved to be significant included perceived usefulness of ADAS. For visual metrics, both the road ahead and dashboard fixation counts were found to be related with a lower minimum time–headway and minimum time–to–collision; for demographics, age and gender proved to be the significant parameters.

When it comes to longitudinal control parameters, acceleration (mean and max.), deceleration (mean and max.), and velocity (mean and max.) were found to be influencing variables. Lateral control parameters included acceleration (mean and max.), deceleration (mean and max.), velocity (mean), position (mean and SD), steering wheel angle (mean and SD). The road environment included rural environment, but also highway (for the gas pedal displacement model). Finally, interventions and distraction were found to highly impact driving performance; for the former (warnings), and similarly to the VRU models, it seemed to be used as an extra margin for safety; therefore it was usually correlated with lower gaps to the cars ahead, while for distraction, usually the opposite effect was noticed, as drivers usually tended to compensate for the higher cognitive load experienced due to distraction. This for example can be witnessed in the increase of braking percentage displacement (max.), or the increase in harsh acceleration [abs.(max.)].

Table 7.1.: Summary of hypotheses tested for VRU panel regression models

	TTC_{min}		Brake pedal displacement (max.)	
Hypothesis	**Validated?**	**Validated in**	**Validated?**	**Validated in**
1: random effects	✓	CE2, CE3, Merged	✓	CE1, CE2
2: individual effects	✓	CE1, CE3, Merged	✓	All
3: attitudes			✓	CE2 (PEU i-DREAMS)
4: visual attention	✓	CE2 (Ped. FC)		
5: socio–demographics	✓	CE2 (Age)	✓	CE1 (Females)
6: longitudinal control	✓	CE2, CE3, Merged	✓	All
7: lateral control	✓	CE1, CE2, Merged	✓	CE1, CE3, Merged
8: road environment	✓	Merged		
9: system warnings	✓	Merged (Rural)		
10: distraction			✓	CE1

	Gas pedal displacement (SD)		Long. acc. [Abs.(max.)]	
Hypothesis	**Validated?**	**Validated in**	**Validated?**	**Validated in**
1: random effects	✓	CE1, CE2, Merged	✓	All
2: individual effects	✓	All	✓	All
3: attitudes			✓	CE1 (PU ADAS), CE2 (PEU ADAS), Merged (PEU i-DREAMS)
4: visual attention				
5: socio-demographics	✓	CE3 (Females)	✓	CE3 (Females)
6: longitudinal control	✓	All	✓	All
7: lateral control	✓	CE2, CE3, Merged	✓	CE1, CE3
8: road environment	✓	Merged (Urban)	✓	Merged (Urban)
9: system warnings			✓	CE3
10: distraction	✓	Merged		

Table 7.2.: Summary of hypotheses tested for tailgating panel regression models

	Headway$_{min}$		**TTC$_{min}$**	
Hypothesis	**Validated?**	**Validated in**	**Validated?**	**Validated in**
1: random effects	✓	CE2, CE3, merged	✓	CE1, CE2, merged
2: individual effects	✓	CE1, merged	✓	CE1, CE2, merged
3: attitudes	✓	CE1 (PU i-DREAMS)	✓	CE1 (PEU i-DREAMS)
4: visual attention	✓	CE3 (Road ahead FC)	✓	CE3 and merged (Road ahead FC)
5: socio–demographics	✓	CE3 (Age)		
6: longitudinal control	✓	All	✓	All
7: lateral control	✓	CE1, CE2, CE3	✓	CE1, CE3, merged
8: road environment	✓	Merged (Rural)	✓	Merged (Rural)
9: system warnings	✓	Merged	✓	CE3, merged
10: distraction	✓	Merged		

	Brake pedal displacement (max.)		**Gas pedal displacement (SD)**		**Long. acc. [Abs.(max.)]**	
Hypothesis	**Validated?**	**Validated in**	**Validated?**	**Validated in**	**Validated?**	**Validated in**
1: random effects	✓	CE2, merged	✓	CE1, CE2, merged	✓	All
2: individual effects	✓	CE1, CE3, merged	✓	All	✓	All
3: attitudes	✓	CE2 (PU i-DREAMS) and merged (PEU i-DREAMS)	✓	CE2 (PU ADAS and PU i-DREAMS)		
4: visual attention					✓	CE2 (Dashboard FC)
5: socio–demographics	✓	CE2 (Females)				
6: longitudinal control	✓	All	✓	All	✓	CE2, CE3, merged
7: lateral control	✓	CE1, CE2, CE3	✓	CE2	✓	All
8: road environment			✓	Merged (Highway)		
9: system warnings						
10: distraction	✓	CE1			✓	CE1

7.1.3. Transferability of findings

Chapter 6 discussed the model findings including the acceptance of the developed system, but also the insights revealed from the models integrating the different datasets. This was based on the data collected in this dissertation (the car driving simulator data in Germany). However, there is a motivation in knowing whether some of the findings could at least be transferred to other modes, a question which can be answered by conducting a similar analysis to the driving simulator datasets from other modes. While not collected in the scope of the dissertation, tram, and truck simulator data were made available within the context of the same case study and were therefore used for discussing the transferability of findings. In particular, the same analysis that was done in Section 6.1 (drivers' perceptions and acceptance models) was repeated using the truck and tram simulator datasets. This section presents the main findings obtained from this analysis, including as well an overview of the qualitative analysis (based on the open-ended questions in the questionnaires), but also discusses whether the technology acceptance model (TAM) can be validated for the multi—modal context. Excerpts from this section are presented in (Al Haddad, Abouelela, Graham Hancox, et al., 2022).

An overview of the multi–modal driving simulator data (based on the design principles elaborated in Section 4.3, in particular in Section 4.3.2) is given in Appendix B, where an overview of the socio–demographics is given, including a high level analysis of the attitudinal statements. Additional plots for the questionnaire statements are also given in Appendix D.2.2, including cars and truck participants' prior exposure to ADAS, attitudes towards ADAS, and perceptions of the i-DREAMS system and its clarity. Moreover, Chi–square tests were conducted to test whether the difference between some of the statements across modes was significant (Appendix D.3.2). In general, it seems that on average, findings were not so different between cars and trucks' ADAS exposure (Figure D.7) and attitudes towards ADAS (Figure D.8). A Chi–square test for ADAS exposure between cars and trucks revealed a significant difference for following ADAS: automatic emergency break, forward collision warning, lane keeping assistance (all of which were more present for truck drivers), and parking assist (more for cars). When looking at perceptions towards ADAS systems, significant differences were observed for perceptions of distraction (overall truck drivers seemed to agree less that ADAS would distract them from driving in comparison with car drivers; 30% vs. around 60%, respectively), driving performance improvement, accident risk reduction, driving behavior maintenance (for all later statements, it seemed that car drivers seemed to have a higher level of agreement on ADAS usefulness, compared to truck drivers). This comparison was not possible with tram drivers, as tram ADAS were not common (more details on the truck and tram questionnaires is given in Fran Pilkington-Cheney et al. (2020)). When looking at drivers' attitudes towards the system, it seems that both car and truck participants found the system clearer visually as compared to auditorily. Still for truck drivers, clarity was overall lower, and mostly auditorily (Figure D.9).

Figures D.10 and D.11 present the results for car and truck driver participants' attitudes towards the i–DREAMS system. Significant differences between the different modes were noted for perceptions on whether people would encourage participants to use the system, whether they would be proud to show it to people, and on whether they knew how to use it. In particular, between car and truck drivers, differences were noted on the perceptions of increased attention induced by using the system, and social perceptions (interactions with people); between car and tram drivers, differences were noted on whether they knew how to use the system or not. As tram drivers did not have common ADAS (exact same ones at least), a closer analysis on questionnaires regarding their risk perceptions revealed that tram drivers were mostly risk averse, perceiving ADAS to be very important overall.

Chi–square test results for the multi–modal driving simulator study are detailed in Appendix D.3.2; Tables D.16 and D.17 present the results for the comparison across modes, where the latter table is a pairwise comparison highlighting for which modes the difference was significant.

Factor analyses were also conducted on the questionnaires' attitudinal statements for truck and tram simulator experiments; results for these analyses are presented in Appendix D.4, in Tables D.18 to D.21. Table D.18 presents the factor analysis results of truck participants' prior perceptions towards ADAS, which resulted in two constructs of ADAS, perceived usefulness and perceived ease of use. Comparing that with the results of ADAS perceptions for car participants (see Table 6.1), similar findings are observed. As already mentioned, tram drivers did not share the same ADAS, therefore this analysis was not also done for the tram data.

Table D.19 presents findings on truck drivers' attitudes towards the i–DREAMS system, which resulted in two main factors, perceived usefulness, and the perceived ease of use. Findings obtained are similar to those of car drivers participants (Table 6.3); noted differences were on perceived ease of use for truck drivers including factors related to perceived system clarity. Similar findings were also observed for tram drivers (Table D.20); for both tram and truck drivers, system annoyance was found to negatively impact perceived usefulness, which was not found for car drivers. Also, when merging all observations for the different modes, similar findings were observed (see Table D.21).

For truck participants, the qualitative analysis of the questionnaires revealed that drivers found the system to be clear, simple, easy to understand, useful (bringing awareness), realistic, and quite timely (warnings on time). The visuals and auditory systems were well perceived. However, there seemed to be a confusion with regards to the numbers on the pictograms. A suggestion was to replace the time in second with distance in meters. Further improvements suggested to integrate the system into the existing dashboard devices, and to increase the size of the display screen. Possible improvements included an improvement in screen resolution, and in road signs recognition (for it to be faster). Moreover, while the auditory system was generally found to be good, there seemed to be a lack of consensus on whether it was loud enough or not, some finding it possibly distracting. An overall suggestion was to possibly reward participants based on their "good" behavior. Participants also praised the "coffee" sign, which they seemed to understand as a warning to stop for a few minutes, to avoid fatigue. Yet, some participants were skeptical about it, stating they would prefer to rely on themselves, to know when they are tired or not. These findings were rather comparable with the insights obtained from car driver participants.

For tram drivers, noted challenges included more demanding driving during rush hours, due to the presence of additional road users, including pedestrians, school children, scooters, delivery riders, bikes, or other vehicles. Additionally, bad weather conditions were indicated as a factor making driving more demanding, such as having wet, or frosty (and therefore slippery) roads. Finally, fatigue was mentioned, mostly when driving long continuous hours (consistent environments without much change, leading to repetition), or due to very early or very late shifts. Among the ADAS investigated, Drivers Safety Device, Correct Side Door Enabling, Emergency Stop Button, and Emergency PAN (pantograph) Down button were found to be useful, reliable, important and essential; the latter though less used. The overspeeding aid was found to be necessary, positive, with a few saying that it was distracting. Finally, the guardian received some skepticism; while many found it to be useful, some found it distracting and unreliable. Wishes for additional safety systems included warnings for: upcoming signals or bends, speed limits and overspeeding, proximity to pedestrians or other vehicles (collisions), obstacles or object detection in swept path. Moreover, tram drivers indicated their wish for louder warnings, but also for improvements for the current "guardian" system. Overall, while some findings were comparable for tram drivers, it is clear that some insights are mode–specific such as the ones in relation with the ADAS used, but also the mode–specific challenges, including but not limited to fatigue.

Finally, in investigating the technology acceptance model transferability, the hypotheses drawn in Figure 3.1 were tested, with a similar approach as the one followed in Section 6.1., for which the behavioral intention to use the system was validated for cars and trucks. The first hypothesis, testing the relation between the behavioral intention to use and the perceived usefulness and ease of use (both generated from the factor analyses results), has been validated for truck drivers (as was already validated for car drivers) by developing an ordinal logit model with the intention to use as a dependent variable, and the perceived usefulness and ease of use as the independent variables. For tram participants, this was tested both using the tram dataset alone, or a merged dataset with the different modes (for which the mode type was used as a dummy variable), but could not be validated.

The second hypothesis was developed by developing ordinal least squares using the perceived usefulness as a dependent variable; the results however could not validate this hypothesis for either truck or tram participants. For the third hypothesis, each of the perceived usefulness and perceived ease of use was tested as a function of external variables. However, for this hypothesis, a merged model could not be developed as external variables among different modes (for instance demographics) were not common; therefore, these hypotheses were tested for each dataset mode separately. Perceived usefulness was found to be a function of prior perceived usefulness of ADAS, for each of the car and truck datasets, but was not validated for the tram data. Further, perceived ease of use was found to be a function of external variables for all modes; it was strongly related to having previously had fines for truck drivers, and drivers' age for tram drivers. Therefore, the latter relation for each of truck and tram drivers was comparable to the one previously observed for car drivers, for which a relation was found with driver's license duration, or in other words driving experience or history. As a summary, we can say that the technology acceptance model was mostly validated for truck drivers, as was done for car drivers, validating the different links except the second hypothesis (based on the hypotheses laid in Figure 3.1). For tram drivers, only one of the hypotheses was validated. A summary of the findings is given in Figure 7.2, which is an extension of Figure 7.1, adding where possible the modes for which the different links were validated. Essentially, we can see that findings were mostly transferred between car and truck drivers, but not to tram drivers (based on the models, although based on the qualitative analysis, some findings were found to be common). This makes sense, as rail transport has mode–specific particularities. These findings can lay the ground for future work on mode–specific transferability, which would possibly help better scope multi–modal studies.

Note: For the perceived usefulness ADAS for the different modes, it is important that the ADAS refer to the mode–specific ADAS. For cars and trucks, these are quite similar, however for trams, these are different.

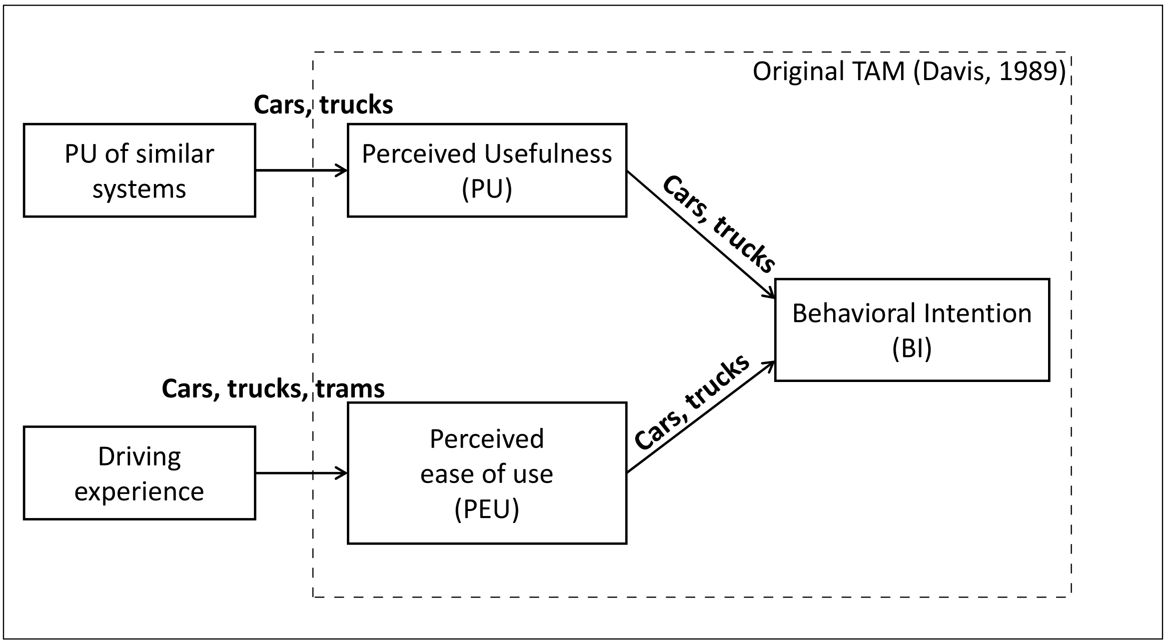


Figure 7.2.: Validated TAM based on the multi–modal driving simulator experiments *(own illustration)*

7.2. Thesis findings and contributions

This dissertation has followed a set of methods (presented in Chapter 3), applied to the experimental case—study (Chapter 4), based on which data has been collected and analyzed (Chapter 5) and then modeled (Chapter 6). In this process, the research questions and objectives initially drawn in the introduction (Section 1.3) have been reached as follows, leading to the contributions of this work (that have been presented in Section 1.4).

1. **Objective 1: data—knowledge–information cycle** has been tackled in Section 2.1, which is partially presented in Al Haddad and Antoniou (2022). Data is often collected by means of various methods and equipment, often combining vehicle data, environment and context data, and driver data. These can be further classified as dynamic or static, subjective, or objective, depending on the features collected. In understanding the nature of this data, it is important to note that driver data is at the intersection between objective and subjective data, but also static and dynamic data. Data collection comes with various challenges, such as data size, which imposes the development of certain protocols to control data quality (for both data collection, and data processing), but also to reduce data and extract the relevant features. A data–knowledge cycle can come in handy to better represent features of analytics and fusion, for driving behavior modeling. The first component is a data analytics framework, starting from a data collection component (with different sources of data: static, dynamic, etc.), followed by a data processing component (with detailed suggested tasks for quality, format, reduction, and data pseudonymization for data protection purposes), then a data storage component (with different storage strategies), and ending with a data mining and analytics component. Additionally, overarching principles or external considerations including ethical, legal, and data protection, overrule and provide guidelines for the different components, eg., pseudonymization before storing and uploading the data, but also regarding data sharing and access to other parties etc. Besides the data analytics framework, data fusion methods adapted from Akbar et al. (2018) were highlighted for use according to the desired objectives. Here an example of fusion for ADAS acceptance across various road transport modes was given. Despite limited research in other sectors focusing on driving behavior, different transport modes can arguably learn from each other, as suggested in Papadimitriou et al. (2020).

2. **Objective 2: standard data handling protocols** have been drafted in Section 2.2, including protocols for the adequate data collection, preparation, storage, and legal and ethical considerations and are presented partially in Al Haddad, Alam, et al. (n.d.).

3. **Objective 3: experiments have been designed** to study relevant research questions; the entire experimental set—up is presented in Chapter 4, including the design of the various simulator and on-road experiments, along with an elaboration of the different data collection instruments used, including eye tracking glasses. In particular, car driving simulator experiments studying VRU interactions, tailgating, and distraction are presented in Section 4.3, with practical aspects elaborated in Section 5.1.

4. **Objective 4: data collected has been analyzed and modeled** and presented in Chapters 5 and 6. The different data sources (eye tracking, simulator, and questionnaire data) have been integrated in panel regression models to assess driving behavior in different situations, such as VRU interactions or tailgating (see Chapter 6). Various hypotheses have been drawn to understand the impact of different factors on driving in different

situations. In particular, human factors including attitudes and perceptions have been found to highly influence driving behavior; this included perceptions (or prior attitudes) towards ADAS, but also demographics like age and gender and driving history. Individual-specific factors in panel regression models have been found to capture part of the models' variability, and therefore proved to be non-negligible. Furthermore, comparing driving performance metrics with and without intervention—based systems showed the impact of the latter on driving (see Tables 5.3 and 5.4 for the results between both conditions). Similarly, distraction has proven to change many of the driving performance metrics, such as lateral control, which usually significantly changed, as a way to compensate for the deteriorating driving performance due to distraction. This was also visible through strongly significant eye movement metrics, but also through the qualitative analysis of the heatmaps. Finally, the assessment of user questionnaires and feedback showed that the acceptance of those systems can be modeled using a classical technological acceptance model, with most relations validated, except the one between PU and PEU; obtained external variables of interest included driving history and prior ADAS experience. The system has overall received positive feedback, with participants expressing high level of trust towards it, with intentions to recommend it further. The system's visuals have been revealed to be particularly easy to understand, with some suggestions however for the sound system (including a voice-over assistance system), but also warnings understandability.

5. **Objective 5: transferability of findings** across modes has been assessed and discussed in Section 7.1.3, focusing on transferability for system acceptance, which was then presented in the updated technology acceptance model for the multi—modal simulator data analysis (See Figure 7.2); this transferability analysis is openly available in Al Haddad, Abouelela, Graham Hancox, et al. (2022). Findings revealed strong transferability potentials mostly between car and truck drivers, with similar factor analysis results and extracted factors for ADAS exposure and attitudes; less however was common with tram drivers and experiments, as ADAS of tram systems were quite different and therefore the statements and questionnaires were not always compatible (it was not possible to match some of the responses). Overall, drivers found the system to be clearer visually (than auditorily); perceived clarity was even lower for truck drivers. For presenting results in terms of a TAM, again, car and truck results were more comparable. However, a merged dataset using the different modes revealed that a TAM could be applicable for the different modes, with driving experience as the common external variable that highly impacts PEU; could be fines for trucks, age for tram drivers, and license duration for cars. Overall, still, the experience was rather positive for most drivers, with car and truck drivers having closer common factors as compared to tram drivers.

7.3. Limitations and Future Work

Despite the various contributions of this work, it of course does not come without limitations, which are necessary to acknowledge. To start with, the data handling protocols (presented in

Section 2.2) have their own challenges, mostly as they are to be applied by various countries and institutes. As part of the data collection protocols, many consent (and other) forms were provided (printed) in hard copies, and signed by participants, and would therefore be only locally stored at the premises of each partner, which might pose a burden for their management. In addition, different questionnaires were translated to different languages, which might have its limitations in terms of consistency of data and responses, and could be burdensome for a multi—modal analysis. The data collection itself was highly impacted by the pandemic; the recruitment was therefore a major challenge, as many of the initially registered participants had dropped out. This of course impacted the sample representativeness and size. Future work could therefore focus on overcoming these limitations. For instance, for data challenges, a harmonization between the different data collection stakeholders would tremendously help mitigating inconsistency risks resulting from data heterogeneity; the stakeholders harmonizing and overseeing the entire data collection could ensure that the quality of collected data does not differ across locations. Another point to be tackled in the future would be the data handling and use beyond the data collection or naturalistic experiment timeline: in other words, future research and studies (also stemming from this one) could focus on drafting protocols and guidelines for an open data initiative, with special attention on which portions of the data (anonymized) could be shared with the wider public; such a research direction goes together with the principles of the European Union for open access data.

The analysis results and models (Chapters 5 and 6) have been conducted using aggregate data for the events of interest; future work could focus on developing more dynamic models (time-series ones) using insights obtained from the models developed in this dissertation. A more complete use of the data could include a use of the biometric wristband heart-rate data, which has not been used in this dissertation; arguably, this is more relevant for fatigue studies, commonly used for professional drivers, and long driving hours. Yet, this data can be tested for private car drivers, to see whether it can enrich the developed models. Furthermore, the transferability analysis conducted in this work (see Section 7.1.3) while proving useful for analysis across car and other modes, has only been done for user perception and acceptance of the system; an interest might be to apply the same or similar models as the panel regression ones developed using the car simulator data (see Section 6.2), to a larger scale dataset (including the simulator data from the other modes). Beyond a transferability analysis for modes within the driving simulator context, an interest could also be to assess transferability between the simulator and the real-road environment, where possible. Such a direction would ensure the scalability of the comprehensive and integrated approach presented in this dissertation. The contributions provided in this work, along with the directions for future research, can help better manage future naturalistic studies aiming at an improved understanding of driving behavior, by better using the available resources, integrating the resulting knowledge, for it to become useful and transferable, paving the way towards safer roads, and towards “Vision Zero".

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A. Driving Simulator and Eye Tracking Specifications

A.1. DSS simulator specifications

Table A.1.: DSS simulator specifications, based on Annex 3 of Graham Hancox, Rachel Talbot, Fran Pilkington-Cheney, et al. (2020)

DSS	Car simulator	Truck simulator
Description	Based on Peugeot 206, using OEM parts. Modular and expandable. Easy to transport, assemble and disassemble.	Mock-up or ergonomic truck/bus driving position. Modular and expandable. Easy to transport, assemble and disassemble.
Driver controls	• Fanatec Podium DD1 20Nm force feedback steering motor. • Car steering wheel with CardioWheel Technology. • OEM blinker/light controls. • Fanatec Clubsport V3 inverted pedals with 90kg Loadcell brake + vibrator on brake and accelerator. • Fanatec Clubsport SQ V1.5 man/seq Shifter	• Fanatec Podium DD1 20Nm force feedback steering motor. • Truck steering wheel with CardioWheel Technology. • OEM blinker/light controls. • Fanatec Clubsport V3 pedals with 90kg Loadcell brake + vibrator on brake and accelerator. • Fanatec Clubsport SQ V1.5 man/seq Shifter
Frame material	Aluminium T-slot profile	Aluminium T-slot profile
Frame dimension, excl. TV's	Length: 1800mm Width: 1350mm	Length: 1300mm Width: 800mm
Full dimensions, incl. TV's	Length: 1800mm Width: 3300mm Height: 1550mm	Length: 1300mm Width: 3300mm Height: 1550mm
Visual	3x Samsung Q70R 49inch TV, 135° Horizontal FOV	3x Samsung Q70R 49inch TV, 135° Horizontal FOV
Instrumentation	Original Instrument Cluster	TBD
Software	STISIM Drive 3	STISIM Drive 3
PC specifications	Intel i7 9700K GeForce RTX 2070 Super 16GB DDR4 RAM 512 GB SSD	Intel i7 9700K GeForce RTX 2070 Super 16GB DDR4 RAM 512 GB SSD
Electrical requirements	1 Schuko Type Socket 1x230VAC + PE, protected by an overcurrent device of 16A and residual current device of max. 300mA.	1 Schuko Type Socket 1x230VAC + PE, protected by an overcurrent device of 16A and residual current device of max. 300mA.
Electrical specifications	Max power: 3.2 kW, 14A 230VAC Internally protected by 16A automatic fuse.	Max power: 3.2 kW, 14A 230VAC Internally protected by 16A automatic fuse.

A.2. Driving simulator parameters

Table A.2.: Driving simulator parameters (*source: own, based on DSS specifications*)

Parameter	**Unit**	**Parameter**	**Unit**
Elapsed time	Seconds	Scene viewing angle	Degrees
Longitudinal acceleration	Meters/second^2	Total pitching angle	Radians
Lateral acceleration	Meters/second^2	Total rolling angle	Radians
Longitudinal velocity	Meters/second	Steering wheel angular rate	Radians/second
Lateral velocity	Meters/second	Minimum distance to vehicle in own lane	Meters
Total longitudinal distance travelled	Meters	Minimum distance to vehicle in opposing lane	Meters
Lateral lane position, relative to centerline	Meters	Minimum time to collision in own lane	Seconds
Current driven vehicle lane	/	Minimum time to collision in opposing lane	Seconds
Current roadway curvature	1/Meter	Computer timestamp	Date
Vehicle heading angle	Degrees	Total inertial heading angle	Degrees
Steering wheel angle input	Degrees	Current status of the digital input port on the secondary I/O device	
Longitudinal acceleration due to throttle	Meters/second^2	Current speed limit	Meters/second
Longitudinal deceleration due to brake	Meters/second^2	Number of the most recently activated triggered event	/
Current traffic signal light position	/	Current speed limit	Kilometers/hour
Running compilation of driver crashes	/	Engine rpm value	RPM
Minimum time to collision	Seconds	Clutch pedal input counts	/
Data marker flag	/	Hand wheel torque	Newton meters
Driver vehicle speedometer value	Kilometers/hour	Left indicator state	/
Vehicle yaw rate	Radians/second	Right indicator state	/
Current transmission gear	/	Running compilation of driver tickets	/
Steering input counts	/	Percentage gas pedal	%
Gas pedal input counts	/	Percentage brake pedal	%
Brake pedal input counts	/		

A.3. Driving simulator scenario design

The full scenario design is available in Amini et al. (2021), which provides the detailed events starting and ending points (distance–based).

Table A.3.: Summary of critical events for the car driving simulator experiments

Risk factor	Critical event	Road segment	Description
Tailgating	CE1	Rural	A (car)2 is driving at low speed in front of the driver, while the available gap in the opposite traffic is not long enough for an overtaking maneuver. The (car)1 has to follow for a distance of 300–350m
	CE2	Urban	A (car)2 overtakes (car)1 and suddenly merges into the lane in front of it with the result that (car)1 needs to adjust the driving speed.
	CE3	Highway	A car enters the highway in front of (car)2, with the result that the lead (car)2 needs to make a harsh brake
VRU collisions	CE4	Urban	A pedestrian crosses the road illegally (the traffic light does not permit crossing) when the driver is approaching the intersection on the green phase.
	CE5	Urban	At a mid-block crossing, a pedestrian -initially obstructed from the driver's view by a bus starts crossing the road while the driver is approaching.
	CE6	Rural	A pedestrian - initially obstructed from the driver's view by bushes- crosses the road at the uncontrolled crossing while the car is approaching.

A.4. Eye Tracking (TobiiPro2) background

The concept of visual tracking to study how we gather information via glancing at specific objects has been around since the 1800s (Tobii Pro AB, 2021). An eye tracking device makes use of invisible near-infrared rays and high-definition cameras to project incident light onto the eye and assess the direction of the reflected ray off the eye's cornea (Tobii Pro AB, 2021). Analyzer modules with the appropriate algorithms are then made use of to assess the eye

Table A.4.: Order of traffic environments for simulation configurations

Segment sequence	Configuration A	Configuration B	Configuration C
Segment 1	Rural	Urban	Highway
Segment 2	Highway	Highway	Rural
Segment 3	Urban	Rural	Urban

Table A.5.: Distraction types across critical events

Distance (m)	CE	Distraction type	Text message
1850	CE 6	Reading	"Thank you for participating in the experiment"
4100-4400	CE 2	Reading and replying	"Can you name two cities you want to visit?"
5000	No event	Reading	"Your dentist appointment is scheduled for 30/11/2020 at 14:15"
7500-8500	CE 3	Reading and replying	"Where is your hometown?"
11850-11890	CE 5	Reading	"Nice to see you at the café yesterday"
13150	CE 4	Reading	"50% discount on online orders! Today only!"
14100	No event	Reading and replying	"What are two things you enjoy doing the most?"
14700-15000	CE 1	Reading and replying	"27+32=?"

position and its gaze. The aim is to visually map the subject's gaze behavior. The different modules of the Tobii Pro Glasses are depicted in Figure A.1.

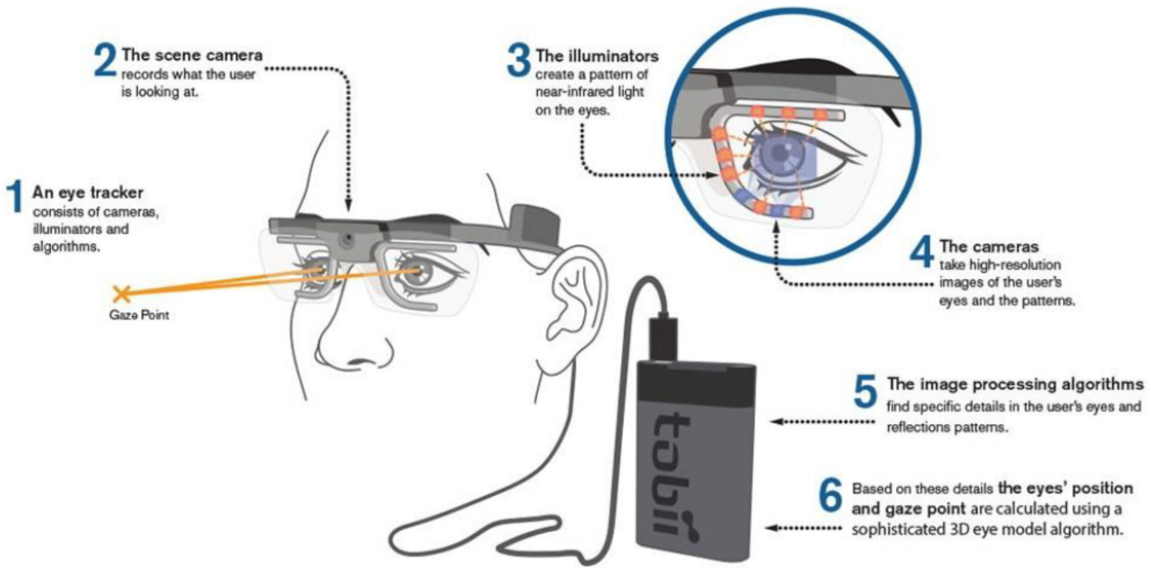

Figure A.1.: Tobii Pro Glasses (Tobii Pro AB, 2021)

B. Multi–modal Driving Simulator Data

This chapter presents an overview of the collected data within the multi–modal driving simulator experiments described in Section 4.3.2. As previously mentioned, only the car simulator experiments conducted in Germany (N=60) have been designed and executed as part of this dissertation.

Table B.1.: Socio–demographic characteristics of the different simulator samples (*source: own*)

Variable		Car (N=60)	Truck (N=36)	Tram (N=28)
Gender	Male	25 (42%)	30 (83.3%)	27 (96.4%)
	Female	35 (58%)	6 (16.7%)	1 (3.6%)
Age		30 (26, 37)	37 (22, 49.25)	47.3 (36, 57.3)
Employment	Full-time	-	-	3 (82.1 %)
	Part-time	-		5 (17.9%)
Weekly kms	<500 km	-	4 (11.8 %)	-
	500 to 1000 km	-	7 (20.6 %)	-
	1000 to 2000 km	-	10 (29.4 %)	-
	>2000 km	-	13 (38.2 %)	-
Fines	None	41 (68%)	11 (33.3 %)	-
	At least one	19 (32%)	22 (66.7 %)	-
Accidents	None	56 (93%)	23 (69.7 %)	-
	At least one	4 (7%)	10 (33.3 %)	-
Working years		-	-	10.2 (3.5, 18)
License years		9 (6, 15)	-	10 (4, 15)

An overview of the demographics reveals findings on the different samples. While gender seems to be balanced for car drivers, this was not the case for truck and tram drivers, who tend to be mostly (exclusively) males; which makes sense as this is commonly the case for professional drivers.

Similarly to car drivers, most fines for truck drivers pertained to overspeeding, the same way accidents resulted in material damage only. Still, it is interesting to note that on average the percentage of truck drives having had at least one fine is double the one for car drivers, the same way the percentage having had an accident is way higher for truck drivers.

In addition to the demographics and variables reported in Table B.1, additional questions were asked on the roadway environments, but also sleep quality, for each of truck and tram drivers. Truck drivers mostly drove on motorways (a distribution of on average 42%), followed by rural (on average 36%), then by urban (on average 27%). Their working time was mostly during the day (53%), followed by a combination of both daytime and nighttime (44%). On the other hand, tram drivers worked an average of 28 hours per week, mostly (71%) in a combination of day and night shifts.

Regarding sleep patterns, it seemed on average that neither truck or tram drivers had main sleep issues, none had previous sleep diseases (except one tram driver who had sleep apnea). Both truck and tram drivers indicated that their sleep quality was mostly mostly good or very good (about 64% of drivers), while only 21% of truck drivers revealed that their sleep quality was not so good, as opposted to 18% for tram drivers. The majority of truck drivers (61% or 20 out of 33 drivers), only very occasionally (less than 2 to 4 times per month in the last year) had to fight sleep to stay awake, as opposed to only 12% of them indicating that they never had to do so in the past year. For tram drivers, the last two figures were 57% and 36%, respectively.

Most truck drivers (52%) never had to stop driving due to drowsiness in the past year, and about 21% of them had to do so more than three times that year. The percentages were similar for drivers who wanted to stop driving due to drowsiness, but were not able to do so at that time; On the other hand, no tram drivers indicated that they had to stop because of feeling sleepy. Only one person indicated that they wanted to stop the tram but were unable to (3.6%). The last figures indicate that truck drivers on average struggled more with sleep, which makes sense due to longer travelled distances, but also as they have more the opportunity, compared to tram drivers, to stop in case of drowsiness.

Finally, very few truck drivers indicated that in the past year they fell asleep while driving (only one driver), as opposed to no tram drivers; also, only one driver indicated that they had a sleep–related incident in the past year (incident due to falling asleep while driving), as opposed to only two tram drivers (who had an incident over the past 10 years).

Remarks:

- *While the statistics intend to be for the entire sample (N=36 for example for trucks), for some variables, there were some missing values (usually 1 or 2 at most); for those, the N was not 36 naturally, therefore the statistics are provided both in absolute values, but also in percentages. Moreover, provided statistics are usually percentages, but also sometimes the interquartile range, for variables whose answer options were continuous and not discrete, such as age, number of years worked, or number of years since acquiring the license.*
- *Both "Fine" and "Accident" variables refer to the last three years of using the truck or the car.*
- *Weekly kilometers is an estimate of the mileage using the truck.*
- *The variables fines, accidents, working years and license years refer to the main mode investigated. For instance, even if truck drivers also drive cars, the reported numbers refer to accidents or fines or working years as a truck driver; the same applies for tram drivers.*

C. Forms and Questionnaires

Forms and questionnaires used for the data collection in the car simulator experiments are given in this Appendix. Section C.1 first provides an overview of the created forms, including the participant information sheet and consent forms (to collect and use the data), a debriefing form (to highlight that texting while driving, which was part of the experiment, was only done for the purpose of research, and is not an acceptable behavior in real driving conditions), and a participant payment voucher form.

Section C.2 then provides an overview of the different questionnaires, including first the recruitment questionnaire [conducted online through the university Wikipedia system (https://wiki.tum.de/)], followed by the various questionnaires [entry questionnaire, and exit questionnaires A and B, all of which have been deployed online, using LimeSurvey (https://www.limesurvey.org/de/)].

It is important to note that these forms and questionnaires were available in both English and German, depending on the participants' preferences; in this appendix, the forms and questionnaires are only provided in English.

C.1. Forms

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 814761.

Participant Information Sheet and Participant Consent to: i-DREAMS: Driving simulator experiments.

Dear participant,

You are taking part in i-DREAMS (a smart Driver and Road Environment Assessment and Monitoring System) scientific research study. In this information sheet, you can find all necessary information relating to it.

At least 30 participants are taking part in this study. The study is led by the Chair of Transportation Systems Engineering at the Faculty of Civil, Geo, and Environmental Engineering at the Technical University of Munich. It is funded through the EU horizon 2020, Grant No. 814761, i-DREAMS.

This study has been reviewed by the TUM Ethics Commission, which raised no objections against the study during consultation (Approval number: 78/20 S).

Your participation is completely voluntary. You can withdraw from the study if you do not wish to participate or withdraw your consent without any consequences at any time.

We ask you to carefully read this information sheet. The study supervisor will brief you about the study and answer any questions you may have.

Why is the study conducted?

The aim of the experiment is to test driver safety under specific conditions. Risk factors are tested in a simulator environment to evaluate driving behavior under specific risk conditions. The expected benefit is to investigate whether real time warnings can improve driving behavior.

What is the procedure?

Your participation to the study ends after this session.

Your participation will last one to two hours and includes, 1) filling questionnaires regarding your socio-demographic characteristics, your driving experience, your attitude towards safety and driving in general, and 2) driving in a simulator, as you would in the real world. The following equipment will be used:

- A steering wheel (CardioWheel), which measures your heart rate; the position of your hand on the steering wheel will determine stress, fatigue, and distraction while driving
- A front camera (Mobileye), which records the simulated environment (e.g. road environment, pedestrians, distance to the vehicle in front, lane position, etc.)
- Tobii Pro 2 Glasses, wearable eye-trackers/glasses, which collect eye movement data, e.g. the glance direction.

What are your benefits from participating in this study?

Participation in this study does not have any particular benefits for you. Rather, the results of the study could in the future help all people, by improving road safety.

What are the risks associated with your participation in this study?

The participation in this study does not expose you to any risks.

Do you receive any compensation?

As a thank you for your participation, you will receive a voucher worth 25 Euros.

Can you drop out of this study?

Your participation to this study is voluntary. You can end your participation at any time, without the need of justification. In this case, you do not get any compensation.

Your data would then be deleted unless you consent to the use of your anonymized data. After anonymization, it is not possible to delete your data, as we would not be able to relate it to your identity.

Data protection information

In this study, the Chair of Transportation Systems Engineering at the Technical University of Munich is responsible of the data handling. Processing your data is only allowed upon your consent. Your data will only be collected for the purpose of this study and used within the scope of this study.

The collected data includes personal data like name, address, and birth date. Sensitive data is not collected, with the exception of your nationality, health status, attitudes, and perceptions. The data that directly identifies you like name, address, etc., would be replaced by an identification code (pseudonym).

Your data would be saved in a server in Germany. Your personal data will be deleted at most five years after the end of the project, and therefore your data will become anonymized.

Only the pseudonymized data (protected) would be shared among other partners in this project, who have the same data agreements.

Data used for publications would not identify you personally. Following the EU open data strategy, a fully anonymized portion of the data could be made publicly available.

The consent to the processing of your data is voluntary. You can revoke your consent at any time for the future without affecting the legality of the processing carried out on the basis of the consent until the revocation on the basis of Art. 6 para. 1 lit. a DSGVO. After your revocation, your personal data will be deleted immediately. Please address your revocation to Prof. Dr. Constantinos Antoniou (c.antoniou@tum.de) or Ms. Christelle Al Haddad (christelle.haddad@tum.de).

Under the legal conditions, there is a right of access, as well as a right to rectification or deletion or to restriction of processing or a right to object to processing, as well as the right to data portability. There is also a right of appeal to the Bavarian State Commissioner for Data Protection.

In such cases, please contact:

Chair of Transportation Systems Engineering , Prof. Dr. Constantinos Antoniou (c.antoniou@tum.de) or Ms. Christelle Al Haddad (christelle.haddad@tum.de).

In case of a complaint, please contact:

Data Protection Officer of TUM

Technische Universität München

Arcisstr. 21 , 80333 München

E-Mail: beauftragter@datenschutz.tum.de

Or:

Bavarian State Commissioner for Data Protection

Postal address: Postfach 22 12 19, 80502 München

Office address: Wagmüllerstr. 18, 80538 München

E-Mail: poststelle@datenschutz-bayern.de

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Participant information and consent to the project: i-DREAMS Participant consent

Consent to participation

I was informed about the study by ___________________________. I have read the participant information and participant consent regarding the above study. I also received detailed information (written and oral) regarding the objective and procedure of the study, risks of my participation, my rights, and my obligations. I had the chance to ask questions and received satisfactory responses. Besides the written information, the following points were discussed:

____

I was informed that my participation is voluntary and that I have the right to withdraw at any time without the need for justifications and without any disadvantages.

I hereby consent to the participation of the above study.

____

Participant name in capital letters

____

Place, date Participant signature

____

Supervisor name in capital letters

____

Place, date Supervisor signature

Consent to data processing

The processing and use of my personal data for the study exclusively follows the described information.

I hereby consent to the described processing of my personal data.

____

Place, date Participant signature

____

Place, date Supervisor signature

3/3

Technical University of Munich

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 814761.

Dear participant,

Thank you for supporting the i-DREAMS project by taking part in the simulator study and filling out the questionnaires.

As already explained in the information sheet, the conducted experiment is purely for research and the collected data will be handled in accordance with the GDPR regulations.

It is also important to note that the simulator trial in which you were asked to read and reply to text messages aims to better understand the impact of distraction on driving. Using a mobile phone while driving is by all means not allowed and we are not promoting this behavior. This was not mentioned in the information sheet or prior to the experiment in order to not bias the results of the trial.

Please do not hesitate to ask any questions you might have.

I have read and understood the debriefing form regarding the simulator trials and my participation in the study "Safety tolerance zone calculation and interventions for driver-vehicle environment interactions under challenging conditions".

My questions were answered, and I received a copy of this form.

____

Participant name (Capital letters)

______________________________ _________________________

Participant signature **Place, date**

iDREAMS

Technical University of Munich

TUM

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 814761.

Participant Payment Voucher

I participated in the i-DREAMS driving simulator research project on driver performance on

____ /____ /______.
(date)

For my participation in this study, I received a participation voucher worth 25 Euros.

____
Participant name (Capital letters)

________________________________ ___________________________
Participant signature **Place, date**

____
Administrator signature

C.2. Questionnaires

Simulator Study Recruitment Questionnaire

The following questionnaire is intended to assess whether you can participate in the study.

Filling in the questionnaire takes around 5 minutes.

Please answer the questions as honestly and clearly as possible.

Thanks in advance!

* Required

Application form

I. Contact details

With the help of the information below we can contact you for further arrangements regarding this study.

First name *

Last name *

Email address *

Phone number

Mobile or landline

Do you give us your consent to call you at this number?
Yes
No

II. Personal information

Using the data below, we will assess your suitability as a participant for our study.

Gender *
Male
Female
Other

Nationality *

Second nationality
if applicable

Birth year *
e.g. 1990

City of residence *

Do you have a valid driving license? *
Yes
No

If yes, is your driving licence valid in Germany? *
Yes
No

When did you get your driving license? *
e.g. 2010

III. Additional information

We use this information to select those people whose conditions match the objectives of our study.

Do you have a medical problem that can affect your driving performance?
Yes
No

If yes, please specify:

Do you need to wear glasses while driving? *
No
Yes
I wear contact lenses

Have you ever gone through an eye surgery? *
No
Yes, scars are left on my cornea
Yes, scars are left on one of my eyes
Others

IV. Language preference

Choose the language which you prefer for the study sessions? *
English
German
I don't mind

V. Further comments

How did you hear about us?
TUM communication (website, linkedin, other)
Social media (Facebook groups, linkedIn)
Friends
Posters
Other

Please let us know, if you have any questions or further comments.

+

Submit

Form: **myFormEnglish**

- View/Edit stored data
- Import API
- Recovery API
- Cleanup API

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement

Simulator study car drivers – Entry questionnaire

Participant ID: Date:

Advanced Driving Assistance Systems (ADAS)

Which ADAS are present in your car?

- Adaptive cruise control
- Forward collision warning
- Night vision and pedestrian detection
- Traffic sign recognition
- Lane keeping assistance
- Blind spot warning
- Drowsiness alert
- Parking assist
- High speed alert
- Automatic emergency braking
- None
- Other: …………………

If you have/share a car in your household, this question applies to you.

How often do you use the following ADAS that are present in your car? (if applicable)

	Almost never	Sometimes	Often	Almost always	Not applicable
Adaptive cruise control					
Forward collision warning					
Night vision and pedestrian detection					
Traffic sign recognition					
Lane keeping assistance					
Blind spot warning					
Drowsiness alert					
Parking assist					
High speed alert					
Automatic emergency braking					
Other: …………………..					

1/4

Indicate to what extent you agree with the following statements about ADAS in general.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
ADAS are useful while driving					
Using ADAS increases my driving performance					
My interaction with ADAS is clear and understandable					
I find ADAS easy to use					
Using ADAS is a good idea					
I can maintain safe driving behavior while using ADAS					
I will feel more comfortable doing other things (e.g., adjusting the radio) with ADAS					
Using ADAS information requires increased attention					
Using ADAS information decreases the accident risk					
I trust the information I receive from ADAS					
ADAS distract me while driving					

Distraction Engagement

	Never	Rarely	Sometimes	Often	Very often
When driving, you:					
converse on a hand-held mobile phone					
manually interact with a phone (e.g., sending texting messages, updating Facebook status)					
adjust in-vehicle devices (e.g., radio, navigation)					
smoke					
converse with passenger(s)					
eating and/or drinking					
read roadside advertisements					
feel fatigue, stressed, unwell					
daydream					

2/4

Indicate to what extent you agree with the following statements about distraction.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
You think it is all right for you to drive and:					
converse on a hand-held mobile phone					
manually interact with a phone (e.g., sending texting messages, updating Facebook status)					
adjust in-vehicle devices (e.g., radio, navigation)					
smoke					
converse with passenger(s)					
eat and/or drink					
read roadside advertisements					
You believe you can drive well even when you:					
converse on a hand-held mobile phone					
manually interact with a phone (e.g., sending texting messages, updating Facebook status)					
adjust in-vehicle devices (e.g., radio, navigation)					
smoke					
converse with passenger(s)					
eat and/or drink					
read roadside advertisements					
While driving you find it distracting when you:					
converse on a hand-held mobile phone					
manually interact with a phone (e.g., sending texting messages, updating Facebook status)					
adjust in-vehicle devices (e.g., radio, navigation)					
smoke					
converse with passenger(s)					
eating and/or drinking					
read roadside advertisements					

3/4

Accident involvement and traffic offense details

Within the last three years, have you been involved in an accident with your car, which was self-inflicted?

- o Yes, once
- o Yes, two times
- o Yes, three or more times
- o Never

If yes, how severe was this accident / were these accidents?

	Accident 1	Accident 2	Accident 3
Material damage only	☐	☐	☐
At least one person was mildly injured (no hospitalization).	☐	☐	☐
At least one person was severely injured.	☐	☐	☐
At least one person was killed.	☐	☐	☐

Within the last three years, have you been fined for a traffic offense while driving with your car?

☐ Yes ☐ No

If yes, for which offense have you been fined within the last three years? Multiple answers are possible.

- o Speeding
- o Driving under the influence (e.g., alcohol, drugs)
- o Tailgating (unsafe following distance)
- o Using hand-held phone while driving
- o Parking offense
- o Illegal overtaking
- o Running a traffic light
- o Running a stop sign
- o Running a yielding sign
- o Not stopping at a pedestrian crossing
- o Other: ……………………………..

4/4

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 814761.

Simulator study car drivers – Exit questionnaire A

Participant ID: Date:

i-DREAMS system

Indicate to what extent you agree with the following statements about the i-DREAMS system.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Using the i-DREAMS system improves my driving performance.					
If I use the i-DREAMS system, I will reach my destination safely.					
I think the i-DREAMS system is easy to understand.					
I think the i-DREAMS system is annoying.					
Using the i-DREAMS system is a good idea.					
The i-DREAMS system makes driving more interesting.					
I would be proud to show the i-DREAMS system to people who are close to me.					
In general, people who I like would encourage me to use the i-DREAMS system.					
While using the i-DREAMS system I can maintain safe driving behavior.					
I have the knowledge necessary to use the i-DREAMS system.					
I am afraid that I do not understand the system.					
I am confident that the i-DREAMS system does not affect my driving in a negative way.					
Using the i-DREAMS system information requires increased attention.					
The i-DREAMS system distracts me from driving.					
I think using the i-DREAMS system makes me a safer driver.					
I think using the i-DREAMS system makes me more aware of my surroundings (other vehicles, lane position, etc.).					

1/2

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I think I can depend on the i-DREAMS system.					
I will feel more comfortable doing other things (e.g., adjusting the radio) with the i-DREAMS system.					
If I had a choice, I would continue to use the i-DREAMS system.					
I would recommend the i-DREAMS system to other drivers.					

Indicate to what extent you find the i-DREAMS system clear in general.

	Very unclear	Unclear	Neutral	Clear	Very clear
How clear do you find the i-DREAMS system in general?					
Why?					
Suggestions to improve					
How clear do you find the visual symbols of the system in general?					
Why?					
Suggestions to improve					
How clear do you find the sounds of the i-DREAMS system in general?					
Why?					
Suggestions to improve					

2/2

Technical University of Munich

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 814761.

Simulator study car drivers – Exit questionnaire B

Participant ID: Date:

i-DREAMS system

Indicate to what extent you find the following characteristic of the i-DREAMS system useful.

	Not useful at all	Not useful	Neutral	Useful	Very useful
How useful do you find it that the system takes into account distraction?					

What are according to you the strongest points of the i-DREAMS system? Max. 3

1.
2.
3.

What are according to you the points for improvement of the i-DREAMS system? Max 3

1.
2.
3.

Please describe the i-DREAMS system with max. 3 keywords (e.g., visually attractive, complicated)

1.
2.
3.

Thank you for taking part in the i-DREAMS study

1

D. Additional Results

D.1. Additional t–test results

This section presents additional t–test results for each of the VRU (section D.1.1) and tailgating events (section D.1.2). The former presents the t–test results for the pairwise comparison of the different VRU events: the comparison between the first (CE1-Ped-Rural) and second (CE2-Ped-Urban) event (Table D.1), between the first (CE1-Ped-Rural) and third (CE3-Ped-Urban) event (Table D.2, and between the second (CE2-Ped-Urban) and third (CE3-Ped-Urban) event (Table D.3). For the tailgating results (section D.1.2), comparison results are given for the t–tests between the first (CE1-Tail-Rural) and second (CE2-Tail-Highway) event (Table D.4), the second (CE1-Tail-Rural) and third (CE3-Tail-Urban) event (Table D.5, and the second (CE2-Tail-Highway) and third (CE3-Tail-Urban) event (Table D.6). For the tables presented in this section, abbreviations are used for most simulator variables; the full description of these variables is given in Table 5.2.

D.1.1. Metrics comparison across VRU events

Table D.1.: Two–sample t–test results for selected variables between the first (CE1-Ped-Rural) and second (CE2-Ped-Urban) VRU critical event

Category	Variable	Monitoring drive			Intervention drive			Distraction drive		
		CE1	CE2	t-value	CE1	CE2	t-value	CE1	CE2	t-value
Longitudinal control	Long. vel. (mean)	13.65	9.91	4.81	14.23	10.28	7.77	13.77	10.72	4.93
	Long. vel. (max.)	19.57	14.19	7.16	20.02	14.13	12.73	20.50	15.57	5.76
	Long. acc. (mean)	-0.13	-0.16	0.59	-0.26	-0.23	-0.62	-0.15	-0.21	1.12
	Long. acc. (max.)	-3.58	-1.85	-2.59	-3.88	-1.33	-3.99	-3.60	-2.30	-1.95
Lateral control	Lat. pos. (mean)	2.39	6.49	-24.28	2.22	6.46	-33.16	2.25	6.32	-26.10
	Lat. pos. (SD)	0.21	0.13	1.22	0.15	0.14	0.57	0.27	0.24	0.30
	Steer. angle (mean)	-0.02	0.09	-1.73	-0.04	-0.00	-0.38	-0.10	0.09	-1.72
	Steer. angle (SD)	1.05	1.09	-0.22	1.26	1.26	0.00	2.04	1.89	0.37
	Lat. vel. (mean)	0.01	0.00	0.58	0.00	0.00	-1.05	-0.01	0.01	-3.50
	Lat. vel. (max.)	0.04	0.03	0.28	0.05	0.02	0.41	-0.13	-1.04	0.84
	Lat. acc. (mean)	0.00	-0.00	0.85	-0.00	-0.00	-0.56	-0.00	0.00	-1.27
	Lat. acc. (max.)	0.03	-0.02	2.01	-0.08	-0.00	-0.69	-0.12	0.01	-1.48
Driver risk perception	TTC (mean)	184.39	238.73	-0.75	141.98	121.29	0.67	224.27	182.39	1.03
	TTC (min.)	42.96	82.26	-1.05	17.48	30.65	-0.61	21.72	30.38	-0.39
	TTC (SD)	263.30	396.43	-1.24	172.79	509.02	-1.95	237.24	362.78	-1.05
	Gas displ. (mean)	0.37	0.27	4.26	0.35	0.24	5.70	0.35	0.25	3.82
	Gas displ. (min.)	0.03	0.02	0.41	0.01	0.01	0.27	0.03	0.01	0.87
	Gas displ. (SD)	0.27	0.20	4.22	0.28	0.19	6.37	0.26	0.21	2.81
	Brake displ. (mean)	0.11	0.09	2.54	0.12	0.08	4.73	0.11	0.09	2.23
	Brake displ. (max.)	0.54	0.48	1.18	0.59	0.35	4.21	0.58	0.46	2.01
	Brake displ. (SD)	0.14	0.10	2.08	0.15	0.07	4.78	0.13	0.10	2.40
Gaze fixation count	i-DREAMS display	N.A.	N.A.	N.A.	1.10	0.88	0.69	2.63	3.98	-1.96
	Road ahead	37.90	53.68	-6.23	35.47	48.45	-4.48	33.12	39.45	-2.12
	Dashboard	9.02	7.40	1.48	8.18	7.98	0.16	6.82	6.48	0.19
	Pedestrian ahead	6.72	11.82	-6.28	8.03	12.17	-3.91	4.87	8.88	-3.93
Gaze fixation duration	i-DREAMS display	N.A.	N.A.	N.A.	0.25	0.17	1.27	0.78	1.05	-1.19
	Road ahead	12.85	17.32	-6.08	12.49	17.33	-4.90	11.55	13.06	-1.65
	Dashboard	2.72	2.11	1.63	2.50	2.29	0.52	1.86	1.57	0.74
	Pedestrian ahead	2.25	3.41	-4.50	2.77	4.45	-3.66	1.74	2.82	-3.15

Table D.2.: Two–sample t–test results for selected variables between the first (CE1-Ped-Rural) and third (CE3-Ped-Urban) VRU critical event

Category	**Variable**	**Monitoring drive**			**Intervention drive**			**Distraction drive**		
		CE1	**CE3**	**t-value**	**CE1**	**CE3**	**t-value**	**CE1**	**CE3**	**t-value**
Longitudinal control	Long. vel. (mean)	13.65	11.21	3.90	14.23	11.84	4.27	13.77	11.75	3.05
	Long. vel. (max.)	19.57	14.45	7.57	20.02	15.09	9.01	20.50	16.40	4.28
	Long. acc. (mean)	-0.13	-0.13	-0.09	-0.26	-0.11	-2.81	-0.15	-0.10	-1.34
	Long. acc. (max.)	-3.58	-3.37	-0.31	-3.88	-2.19	-2.64	-3.60	-2.25	-1.94
Lateral control	Lat. pos. (mean)	2.39	6.36	-19.95	2.22	6.36	-24.78	2.25	6.49	-34.52
	Lat. pos. (SD)	0.21	0.15	0.95	0.15	0.15	-0.05	0.27	0.37	-0.98
	Steer. angle (mean)	-0.02	-0.05	0.43	-0.04	0.01	-0.83	-0.10	0.05	-1.58
	Steer. angle (SD)	1.05	1.29	-0.99	1.26	1.02	0.74	2.04	1.61	1.15
	Lat. velocity (mean)	0.01	0.00	0.96	0.00	0.00	0.06	-0.01	0.00	-2.47
	Lat. velocity (max.)	0.04	0.01	0.67	0.05	0.03	0.33	-0.13	-2.22	1.35
	Lat. acceleration (mean)	0.00	-0.00	1.46	-0.00	-0.00	-0.56	-0.00	-0.00	-0.11
	Lat. acceleration (max.)	0.03	-0.03	2.16	-0.08	-0.01	-0.63	-0.12	-0.05	-0.77
Driver risk perception	TTC (mean)	184.39	468.11	-4.03	141.98	322.72	-6.24	224.27	326.65	-3.00
	TTC (min.)	42.96	100.68	-1.49	17.48	15.35	0.13	21.72	26.69	-0.28
	TTC (SD)	263.30	481.78	-1.97	172.79	409.05	-4.06	237.24	362.79	-2.57
	Gas displ. (mean)	0.37	0.29	3.96	0.35	0.29	3.43	0.35	0.27	3.08
	Gas displ. (min.)	0.03	0.01	1.04	0.01	0.02	-0.89	0.03	0.02	0.16
	Gas displ. (SD)	0.27	0.17	6.05	0.28	0.18	6.51	0.26	0.21	2.96
	Brake displ. (mean)	0.11	0.08	4.13	0.12	0.07	5.31	0.11	0.08	3.90
	Brake displ. (max.)	0.54	0.55	-0.07	0.59	0.39	3.19	0.58	0.43	2.28
	Brake displ. (SD)	0.14	0.10	1.95	0.15	0.07	4.85	0.13	0.08	3.47
Gaze fixation count	i-DREAMS display	N.A.	N.A.	N.A.	1.10	1.52	-1.10	2.63	3.65	-1.64
	Road ahead	37.90	70.18	-9.93	35.47	62.35	-7.28	33.12	42.03	-2.35
	Dashboard	9.02	12.58	-2.60	8.18	11.28	-2.31	6.82	9.30	-1.39
	Pedestrian ahead	6.72	13.15	-6.01	8.03	14.75	-4.65	4.87	7.43	-2.15
Gaze fixation duration	i-DREAMS display	N.A.	N.A.	N.A.	0.25	0.31	-0.71	0.78	1.03	-1.08
	Road ahead	12.85	23.58	-12.96	12.49	23.43	-9.03	11.55	14.91	-2.54
	Dashboard	2.72	3.46	-1.63	2.50	3.37	-2.04	1.86	2.46	-1.32
	Pedestrian ahead	2.25	3.96	-5.45	2.77	5.67	-4.89	1.74	2.69	-2.11

Table D.3.: Two–sample t–test results for selected variables between the second (CE2-Ped-Urban) and third (CE3-Ped-Urban) VRU critical event

Category	**Variable**	**Monitoring drive**			**Intervention drive**			**Distraction drive**		
		CE2	**CE3**	**t-value**	**CE2**	**CE3**	**t-value**	**CE2**	**CE3**	**t-value**
Longitudinal control	Long. vel. (mean)	9.91	11.21	-2.14	10.28	11.84	-3.17	10.72	11.75	-2.08
	Long. vel. (max.)	14.19	14.45	-0.42	14.13	15.09	-1.98	15.57	16.40	-0.93
	Long. acc. (mean)	-0.16	-0.13	-0.74	-0.23	-0.11	-2.82	-0.21	-0.10	-2.69
	Long. acc. (max.)	-1.85	-3.37	2.09	-1.33	-2.19	1.38	-2.30	-2.25	-0.07
Lateral control	Lat. pos. (mean)	6.49	6.36	1.08	6.46	6.36	0.84	6.32	6.49	-1.58
	Lat. pos. (SD)	0.13	0.15	-1.11	0.14	0.15	-0.77	0.24	0.37	-1.17
	Steer. angle (mean)	0.09	-0.05	1.72	-0.00	0.01	-0.20	0.09	0.05	0.54
	Steer. angle (SD)	1.09	1.29	-0.87	1.26	1.02	0.90	1.89	1.61	1.08
	Lat. vel. (mean)	0.00	0.00	1.11	0.00	0.00	1.28	0.01	0.00	0.80
	Lat. vel. (max.)	0.03	0.01	0.58	0.02	0.03	-0.17	-1.04	-2.22	0.62
	Lat. acc. (mean)	-0.00	-0.00	0.53	-0.00	-0.00	0.02	0.00	-0.00	2.88
	Lat. acc. (max.)	-0.02	-0.03	0.35	-0.00	-0.01	0.31	0.01	-0.05	1.19
Driver risk perception	TTC (mean)	238.73	468.11	-2.39	121.29	322.72	-6.19	182.39	326.65	-3.58
	TTC (min.)	82.26	100.68	-0.37	30.65	15.35	0.71	30.38	26.69	0.19
	TTC (SD)	396.43	481.78	-0.65	509.02	409.05	0.55	362.78	362.79	-0.00
	Gas displ. (mean)	0.27	0.29	-0.88	0.24	0.29	-2.94	0.25	0.27	-1.01
	Gas displ. (min.)	0.02	0.01	0.60	0.01	0.02	-1.25	0.01	0.02	-0.75
	Gas displ. (SD)	0.20	0.17	2.34	0.19	0.18	0.70	0.21	0.21	0.22
	Brake displ. (mean)	0.09	0.08	1.71	0.08	0.07	1.13	0.09	0.08	1.90
	Brake displ. (max.)	0.48	0.55	-1.10	0.35	0.39	-0.71	0.46	0.43	0.51
	Brake displ. (SD)	0.10	0.10	0.06	0.07	0.07	0.26	0.10	0.08	1.32
Gaze fixation count	i-DREAMS display	N.A.	N.A.	N.A.	0.88	1.52	-1.87	3.98	3.65	0.43
	Road ahead	53.68	70.18	-4.89	48.45	62.35	-3.62	39.45	42.03	-0.65
	Dashboard	7.40	12.58	-4.06	7.98	11.28	-2.46	6.48	9.30	-1.43
	Pedestrian ahead	11.82	13.15	-1.13	12.17	14.75	-1.59	8.88	7.43	1.05
Gaze fixation duration	i-DREAMS display	N.A.	N.A.	N.A.	0.17	0.31	-1.95	1.05	1.03	0.07
	Road ahead	17.32	23.58	-6.70	17.33	23.43	-4.43	13.06	14.91	-1.30
	Dashboard	2.11	3.46	-3.28	2.29	3.37	-2.74	1.57	2.46	-1.94
	Pedestrian ahead	3.41	3.96	-1.62	4.45	5.67	-1.68	2.82	2.69	0.27

D.1.2. Metrics comparison across tailgating events

Table D.4.: Two–sample t–test results for selected variables between the first (CE1-Tail-Rural) and second (CE2-Tail-Highway) tailgating critical event

Category	Variable	Monitoring drive			Intervention drive			Distraction drive		
		CE1	CE2	t-value	CE1	CE2	t-value	CE1	CE2	t-value
Longitudinal control	Long. vel. (mean)	14.66	20.84	-5.82	15.91	23.89	-8.33	14.84	24.52	-10.31
	Long. vel. (max.)	18.96	26.57	-6.24	19.99	30.34	-10.13	20.46	29.26	-7.88
	Headway (mean)	35.14	31.86	0.30	23.50	25.65	-0.14	180.88	179.05	0.01
	Headway (min.)	16.18	17.48	-0.16	8.57	8.75	-0.03	10.61	170.28	-0.96
	Headway (SD)	25.31	13.54	1.97	22.53	192.79	-0.89	118.60	7.64	1.42
	Long. acc. (mean)	-0.05	0.22	-4.54	-0.01	0.25	-4.89	0.08	0.11	-0.70
	Long. acc. (max.)	-0.28	0.67	-2.14	-0.98	0.12	-2.08	0.22	-0.34	1.06
Lateral control	Lat. pos. (mean)	7.07	11.33	-12.32	7.19	11.74	-19.08	7.16	11.92	-33.04
	Lat. pos. (SD)	0.16	0.30	-2.21	0.13	0.25	-1.80	0.25	0.31	-1.01
	Steer. angle (mean)	0.03	-0.03	1.87	-0.00	-0.03	1.01	-0.06	-0.10	0.35
	Steer. angle (SD)	0.74	0.80	-0.38	0.76	0.69	0.40	1.64	1.12	2.36
	Lat. vel. (mean)	-0.00	-0.01	0.48	0.00	0.00	0.03	-0.00	-0.01	1.53
	Lat. vel. (max.)	-0.00	-0.02	0.32	-0.00	-1.07	0.98	0.00	-0.13	1.64
	Lat. acc. (mean)	-0.00	-0.00	0.36	-0.00	-0.00	1.27	-0.00	-0.00	1.02
	Lat. acc. (max.)	-0.05	-0.06	0.33	-0.02	-0.12	1.31	0.06	-0.14	1.65
Risk perception	TTC (mean)	334.78	361.10	-0.15	231.14	197.81	0.33	724.80	1978.33	-0.80
	TTC (min.)	35.60	41.74	-0.27	24.05	30.97	-0.37	25.72	249.68	-1.01
	TTC (SD)	2675.20	1851.24	0.52	1228.50	1167.14	0.10	4036.57	22088.48	-0.86
	Gas displ. (mean)	0.33	0.54	-5.95	0.36	0.62	-7.12	0.36	0.59	-7.83
	Gas displ. (min.)	0.02	0.19	-4.64	0.02	0.07	-2.08	0.02	0.06	-1.84
	Gas displ. (SD)	0.20	0.22	-1.05	0.22	0.26	-2.02	0.25	0.28	-1.12
	Brake displ.(mean)	0.06	0.06	0.36	0.06	0.06	0.65	0.06	0.06	0.68
	Brake displ. (max.)	0.14	0.11	1.24	0.23	0.11	3.08	0.22	0.11	3.38
	Brake displ. (SD)	0.02	0.01	0.93	0.03	0.01	3.30	0.03	0.01	3.10
Gaze fixation count	i-Dreams display	N.A.	N.A.	N.A.	5.22	4.73	0.50	3.20	4.10	-1.09
	Road ahead	50.47	38.00	3.41	46.25	36.95	2.57	32.63	31.77	0.24
	Dashboard	11.03	7.38	2.82	9.55	6.05	2.88	7.07	4.63	1.83
Gaze fixation duration	i-Dreams display	N.A.	N.A.	N.A.	1.18	1.36	-0.55	0.83	1.05	-0.94
	Road ahead	22.89	16.73	4.10	18.96	15.65	2.53	10.13	11.54	-1.31
	Dashboard	3.27	2.04	2.94	2.97	1.74	2.76	2.05	1.16	2.20

Table D.5.: Two–sample t–test results for selected variables between the second (CE1-Tail-Rural) and third (CE3-Tail-Urban) tailgating critical event

Category	Variable	Monitoring drive			Intervention drive			Distraction drive		
		CE1	**CE3**	**t-value**	**CE1**	**CE3**	**t-value**	**CE1**	**CE3**	**t-value**
Longitudinal control	Long. vel. (mean)	14.66	10.91	8.71	15.91	11.99	7.96	14.84	11.32	6.70
	Long. vel. (max.)	18.96	13.73	7.69	19.99	14.74	7.33	20.46	15.72	5.57
	Headway (mean)	35.14	153.19	-3.13	23.50	64.68	-4.31	180.88	126.55	0.37
	Headway (min.)	16.18	14.42	0.28	8.57	9.16	-0.12	10.61	13.95	-0.48
	Headway (SD)	25.31	379.89	-2.02	22.53	77.37	-6.88	118.60	348.67	-1.16
	Long. acc. (mean)	-0.05	0.02	-2.14	-0.01	0.04	-1.65	0.08	0.01	2.15
	Long. acc. (max.)	-0.28	-0.32	0.09	-0.98	0.43	-2.57	0.22	-0.26	0.77
Lateral control	Lat. pos. (mean)	7.07	2.13	27.59	7.19	2.17	28.15	7.16	2.24	32.04
	Lat. pos. (SD)	0.16	0.18	-0.47	0.13	0.13	-0.20	0.25	0.26	-0.11
	Steer. angle (mean)	0.03	0.10	-1.08	-0.00	-0.00	-0.06	-0.06	0.02	-1.28
	Steer. angle (SD)	0.74	1.50	-1.66	0.76	1.06	-1.74	1.64	1.78	-0.52
	Lat. vel. (mean)	-0.00	0.01	-2.20	0.00	0.01	-1.93	-0.00	0.00	-1.76
	Lat. vel. (max.)	-0.00	0.04	-1.00	-0.00	0.05	-1.85	0.00	-2.18	1.41
	Lat. acc. (mean)	-0.00	-0.00	0.38	-0.00	-0.00	-0.52	-0.00	0.00	-1.22
	Lat. acc. (max.)	-0.05	-0.02	-0.79	-0.02	-0.04	0.57	0.06	-0.00	0.65
Risk perception	TTC (mean)	334.78	1087.72	-2.80	231.14	870.46	-1.95	724.80	384.58	1.35
	TTC (min.)	35.60	43.07	-0.45	24.05	28.32	-0.26	25.72	13.22	1.87
	TTC (SD)	2675.20	7054.92	-1.72	1228.50	6096.95	-1.63	4036.57	1625.90	1.05
	Gas displ. (mean)	0.33	0.28	2.29	0.36	0.31	2.46	0.36	0.29	3.60
	Gas displ. (min.)	0.02	0.01	1.36	0.02	0.02	-0.64	0.02	0.01	0.84
	Gas displ. (SD)	0.20	0.17	2.13	0.22	0.19	2.49	0.25	0.22	1.98
	Brake displ. (mean)	0.06	0.06	0.03	0.06	0.06	0.39	0.06	0.07	-0.57
	Brake displ. (max.)	0.14	0.23	-2.21	0.23	0.21	0.65	0.22	0.31	-1.83
	Brake displ. (SD)	0.02	0.03	-1.67	0.03	0.03	0.86	0.03	0.05	-1.80
Gaze fixation count	i-DREAMS display	N.A.	N.A.	N.A.	5.22	3.02	2.48	3.20	2.08	1.82
	Road ahead	50.47	80.97	-5.18	46.25	64.75	-3.53	32.63	31.43	0.32
	Dashboard	11.03	12.33	-0.86	9.55	11.22	-1.16	7.07	7.05	0.01
Gaze fixation duration	i-DREAMS display	N.A.	N.A.	N.A.	1.18	0.59	3.00	0.83	0.53	1.69
	Road ahead	22.89	28.43	-2.52	18.96	23.88	-2.84	10.13	10.80	-0.62
	Dashboard	3.27	2.91	0.85	2.97	2.81	0.34	2.05	1.88	0.34

Table D.6.: Two–sample t–test results for selected variables between the second (CE2-Tail-Highway) and third (CE3-Tail-Urban) tailgating critical event

Category	Variable	Monitoring drive			Intervention drive			Distraction drive		
		CE2	**CE3**	**t-value**	**CE2**	**CE3**	**t-value**	**CE2**	**CE3**	**t-value**
Longitudinal control	Long. vel. (mean)	20.84	10.91	9.87	23.89	11.99	11.94	24.52	11.32	14.90
	Long. vel. (max.)	26.57	13.73	11.58	30.34	14.74	15.36	29.26	15.72	12.48
	Headway (mean)	31.86	153.19	-3.22	25.65	64.68	-2.38	179.05	126.55	0.31
	Headway (min.)	17.48	14.42	0.46	8.75	9.16	-0.09	170.28	13.95	0.94
	Headway (SD)	13.54	379.89	-2.09	192.79	77.37	0.61	7.64	348.67	-1.88
	Long. acc. (mean)	0.22	0.02	3.69	0.25	0.04	4.42	0.11	0.01	2.60
	Long. acc. (max.)	0.67	-0.32	2.03	0.12	0.43	-0.62	-0.34	-0.26	-0.13
Lateral control	Lat. pos. (mean)	11.33	2.13	28.32	11.74	2.17	32.74	11.92	2.24	48.21
	Lat. pos. (SD)	0.30	0.18	1.73	0.25	0.13	1.77	0.31	0.26	0.53
	Steer. angle (mean)	-0.03	0.10	-1.87	-0.03	-0.00	-0.86	-0.10	0.02	-1.40
	Steer. angle (SD)	0.80	1.50	-1.53	0.69	1.06	-2.20	1.12	1.78	-2.91
	Lateral velocity (mean)	-0.01	0.01	-1.18	0.00	0.01	-0.53	-0.01	0.00	-2.65
	Lateral velocity (max.)	-0.02	0.04	-1.18	-1.07	0.05	-1.03	-0.13	-2.18	1.32
	Lat. acc. (mean)	-0.00	-0.00	-0.02	-0.00	-0.00	-1.44	-0.00	0.00	-1.91
	Lat. acc. (max.)	-0.06	-0.02	-0.92	-0.12	-0.04	-0.94	-0.14	-0.00	-1.46
Risk perception	TTC (mean)	361.10	1087.72	-2.39	197.81	870.46	-2.11	1978.33	384.58	1.02
	TTC (min.)	41.74	43.07	-0.06	30.97	28.32	0.14	249.68	13.22	1.07
	TTC (SD)	1851.24	7054.92	-2.19	1167.14	6096.95	-1.65	22088.48	1625.90	0.98
	Gas displ. (mean)	0.54	0.28	7.52	0.62	0.31	8.92	0.59	0.29	10.94
	Gas displ. (min.)	0.19	0.01	5.00	0.07	0.02	1.78	0.06	0.01	2.42
	Gas displ. (SD)	0.22	0.17	2.52	0.26	0.19	4.41	0.28	0.22	2.93
	Brake displ. (mean)	0.06	0.06	-0.35	0.06	0.06	-0.26	0.06	0.07	-1.23
	Brake displ. (max.)	0.11	0.23	-3.50	0.11	0.21	-3.36	0.11	0.31	-4.98
	Brake displ. (SD)	0.01	0.03	-2.62	0.01	0.03	-3.44	0.01	0.05	-4.97
Gaze fixation count	i-Dreams display	N.A.	N.A.	N.A.	4.73	3.02	1.94	4.10	2.08	2.57
	Road ahead	38.00	80.97	-7.74	36.95	64.75	-5.62	31.77	31.43	0.10
	Dashboard	7.38	12.33	-3.45	6.05	11.22	-3.87	4.63	7.05	-1.49
Gaze fixation duration	i-Dreams display	N.A.	N.A.	N.A.	1.36	0.59	2.55	1.05	0.53	2.35
	Road ahead	16.73	28.43	-5.99	15.65	23.88	-5.21	11.54	10.80	0.76
	Dashboard	2.04	2.91	-2.37	1.74	2.81	-2.99	1.16	1.88	-1.81

D.2. Additional plots

D.2.1. Car simulator questionnaire plots

In this sub–section, additional plots based on the questionnaire analysis or the car driving simulator experiments are provided; these plots present participants' exposure to ADAS (Figure D.1), frequency of ADAS use (Figure D.2), and distraction engagement when driving (Figures D.3 to D.6).

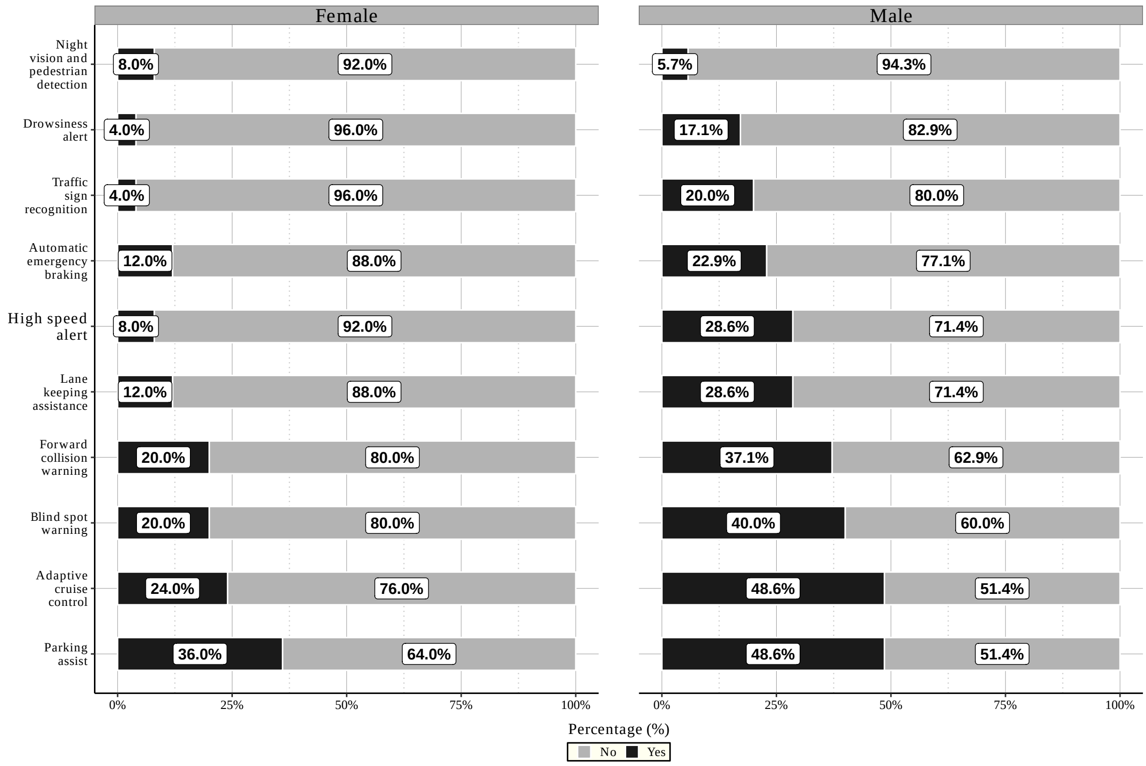

Figure D.1.: Car participants' exposure to ADAS (N=60)

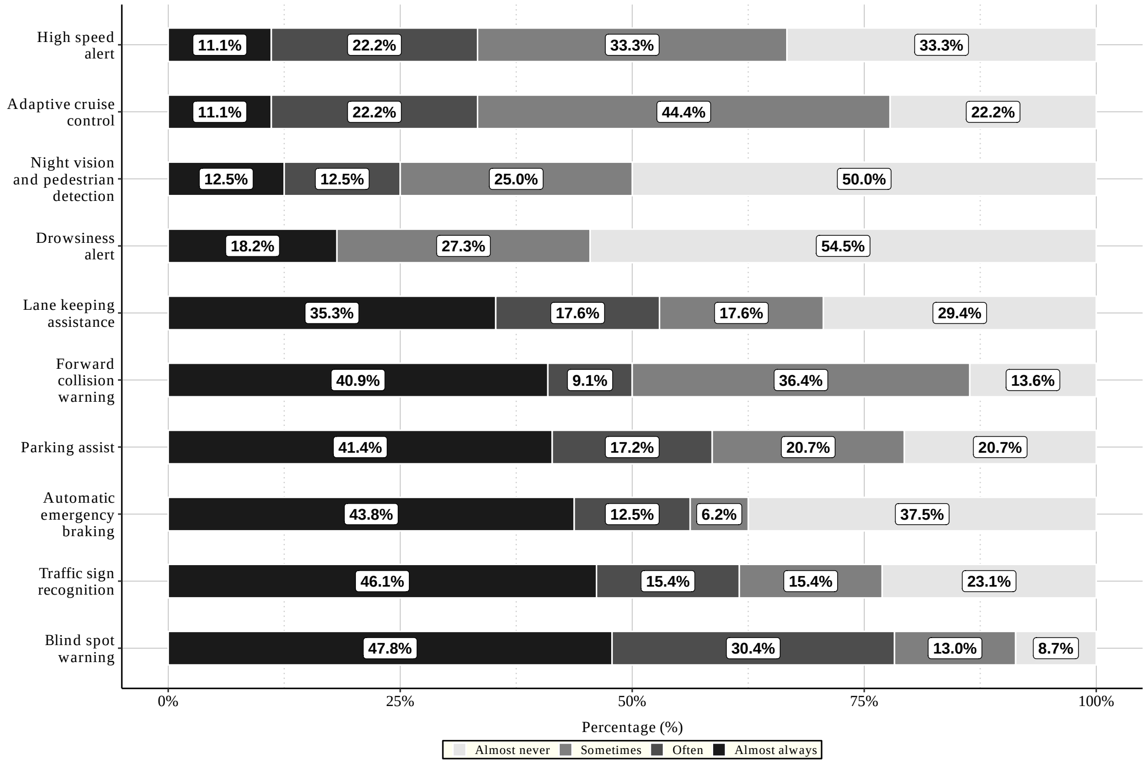

Figure D.2.: Car participants' frequency of ADAS use (N=60)

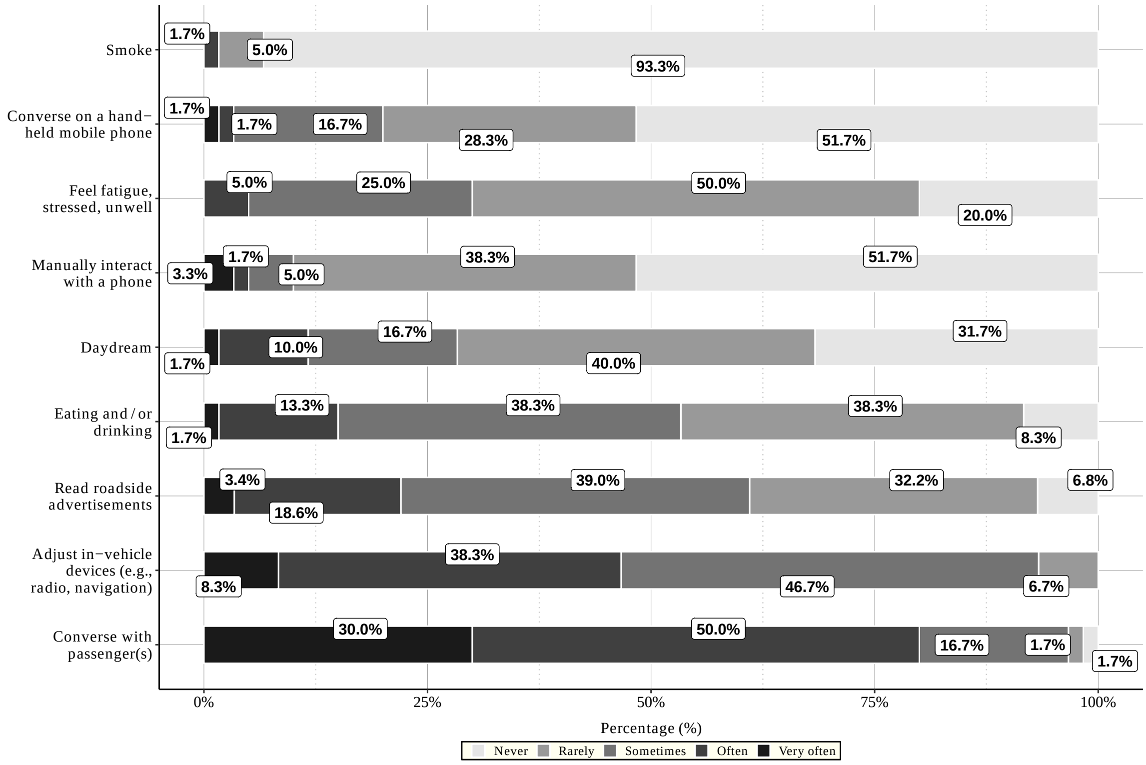

Figure D.3.: Car participants' distraction engagement while driving (N=60)

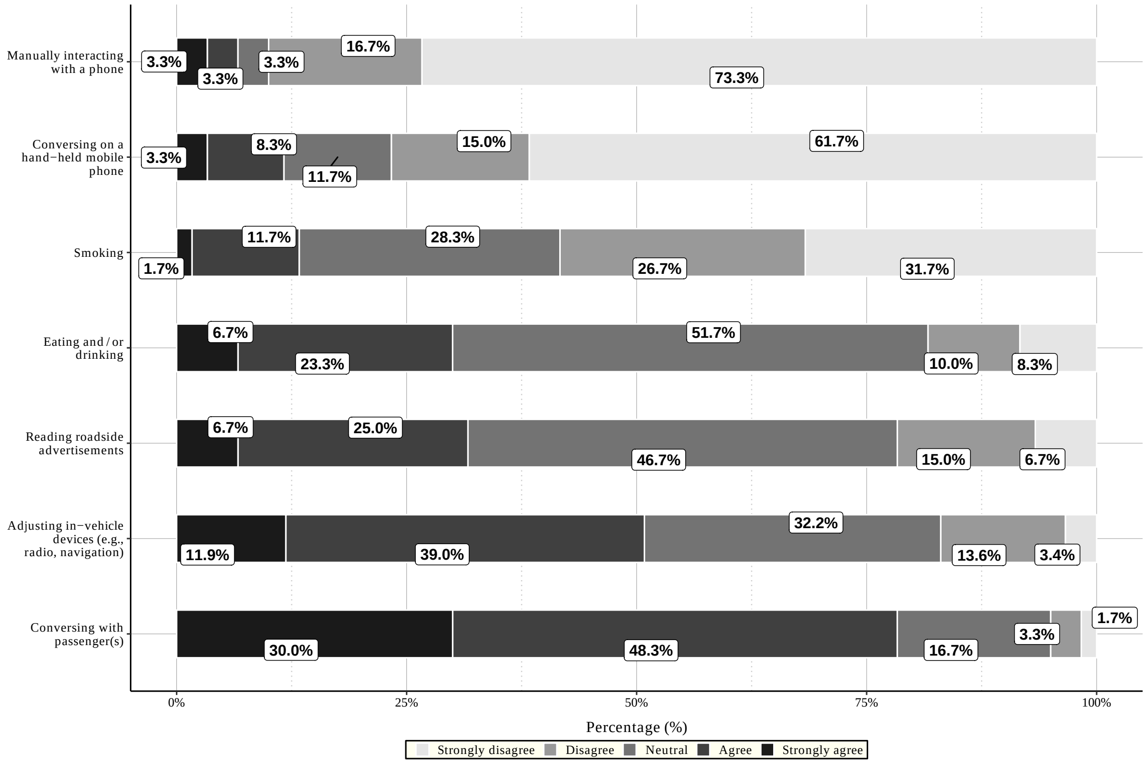

Figure D.4.: Car participants' perceptions of acceptable activities to do while driving (N=60)

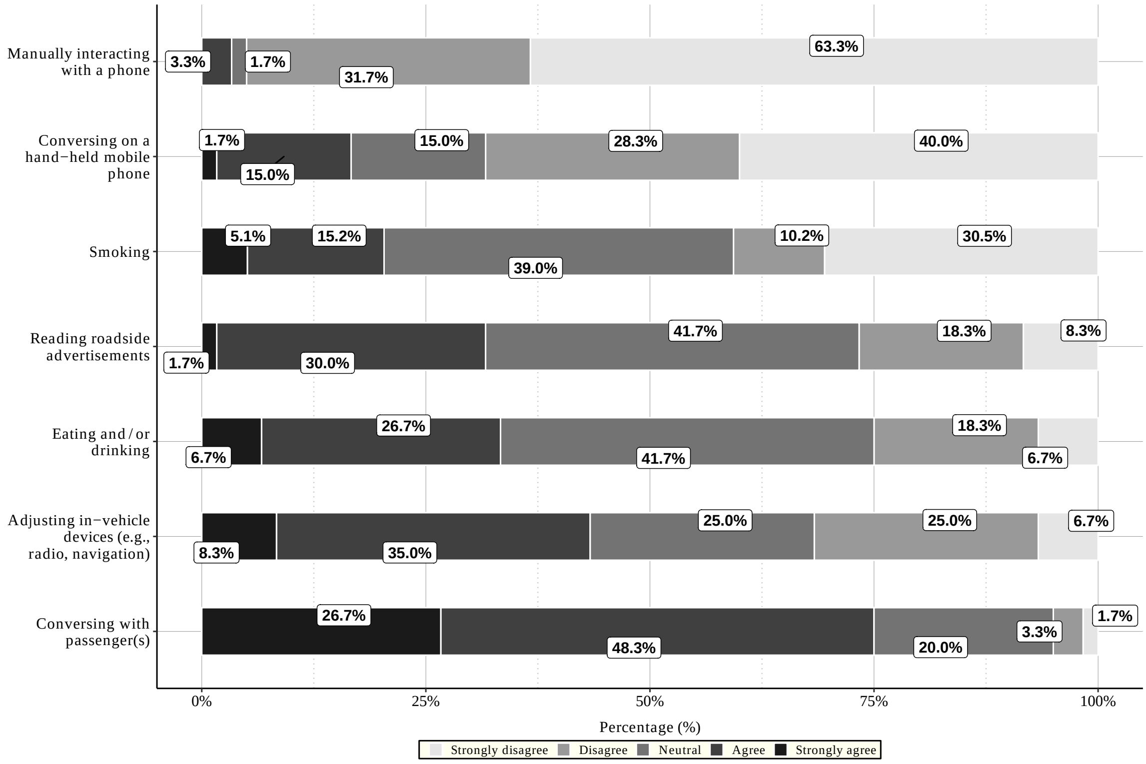

Figure D.5.: Car participants' perceptions of activities that can be done while maintaining a good level of driving (N=60)

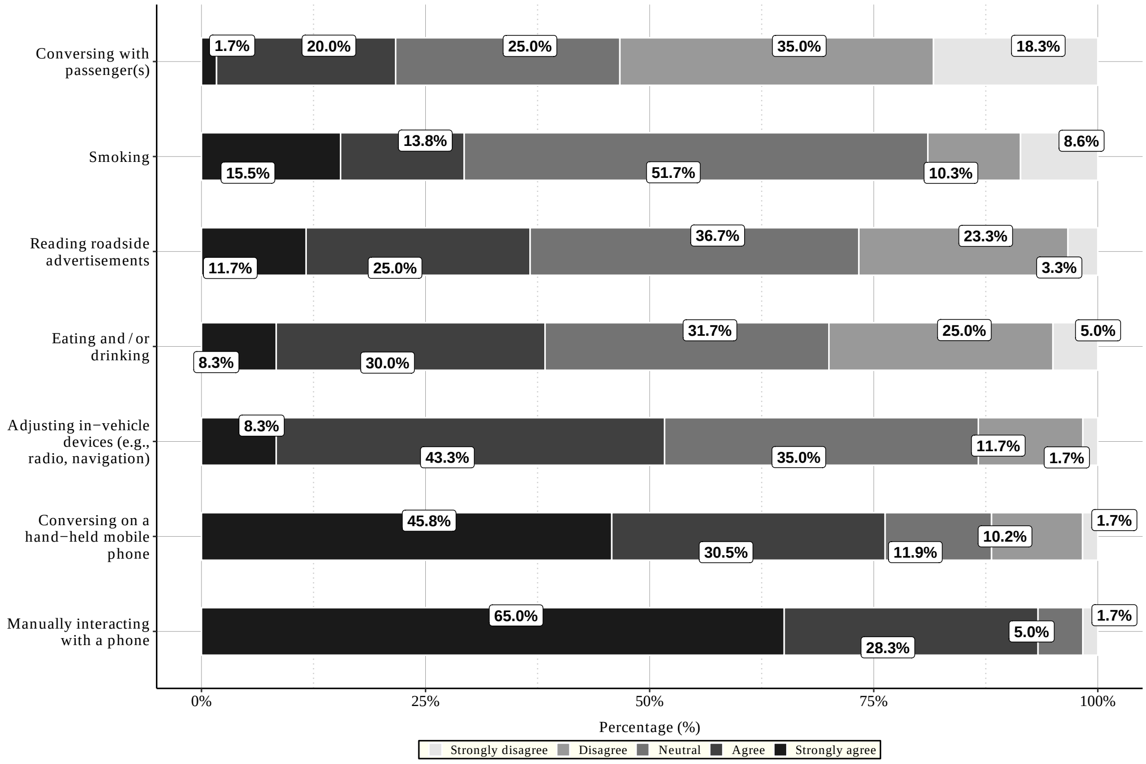

Figure D.6.: Car participants' perceptions of distracting activities while driving (N=60)

D.2.2. Multi–modal simulator questionnaire plots

In this sub–section, additional plots based on the questionnaire analysis or the driving simulator experiments in different modes are provided; these plots present participants' exposure to ADAS (cars and truck participants–Figure D.7), attitudes towards ADAS (cars and trucks–Figure D.8) perceptions of the system clarity (cars and trucks–Figure D.9), and perceptions towards the i–DREAMS system (cars and truck participants, split across two figures, starting from the statements with the highest levels of significance for the Chi–square tests across modes–Figures D.10 and D.11).

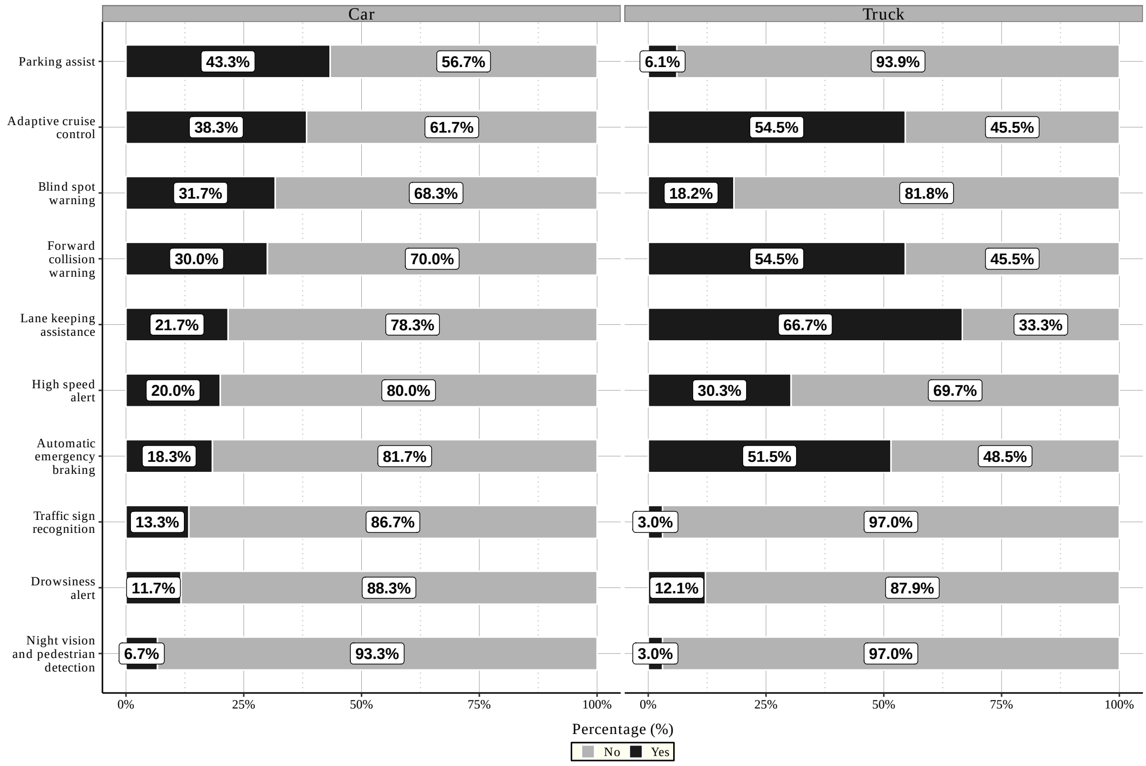

Figure D.7.: Car (N=60) and truck (N=36) participants' exposure to ADAS

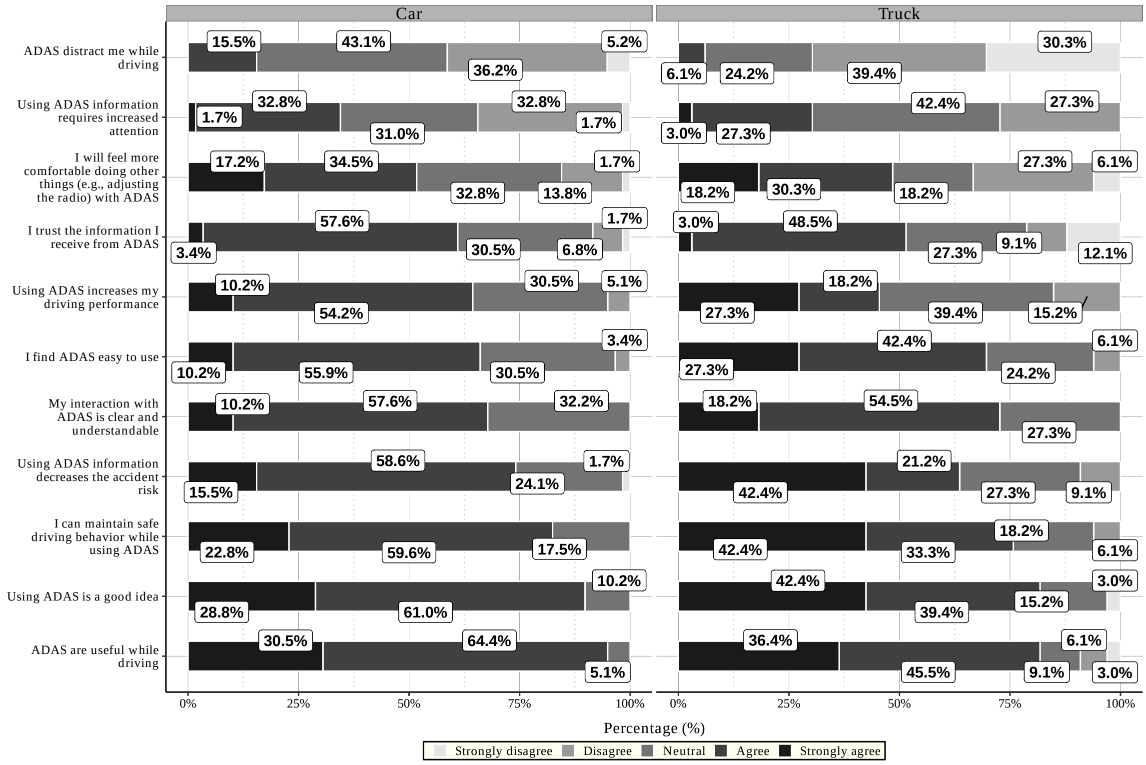

Figure D.8.: Car (N=60) and truck (N=36) participants' attitudes towards ADAS

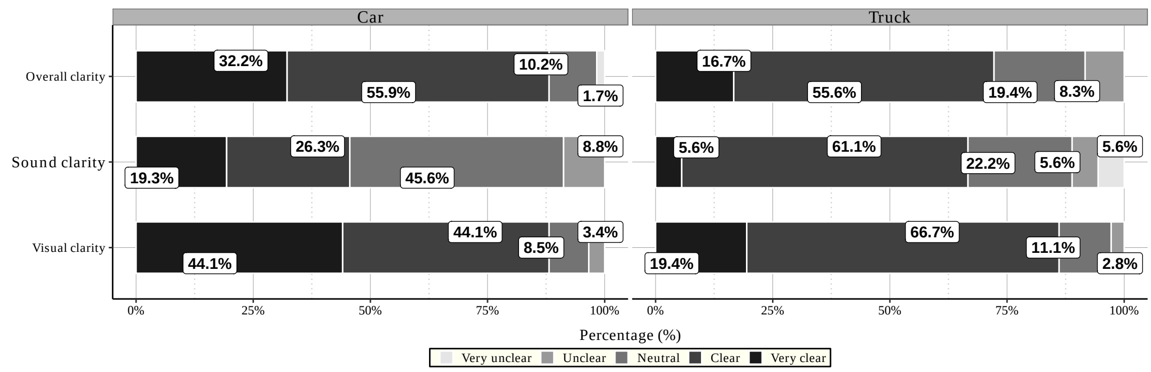

Figure D.9.: Car (N=60) and truck (N=36) participants' perceptions of the system clarity

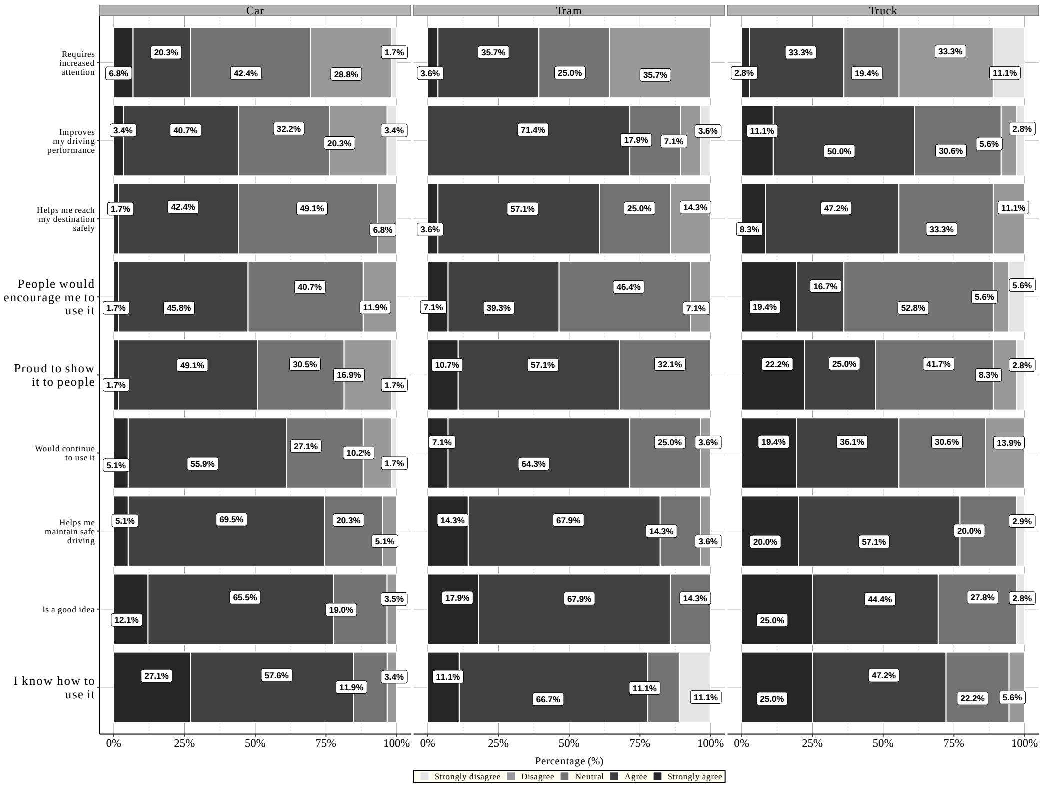

Figure D.10.: Car (N=60), tram (N=28), and truck (N=36) participants' perceptions of the system (part 1)

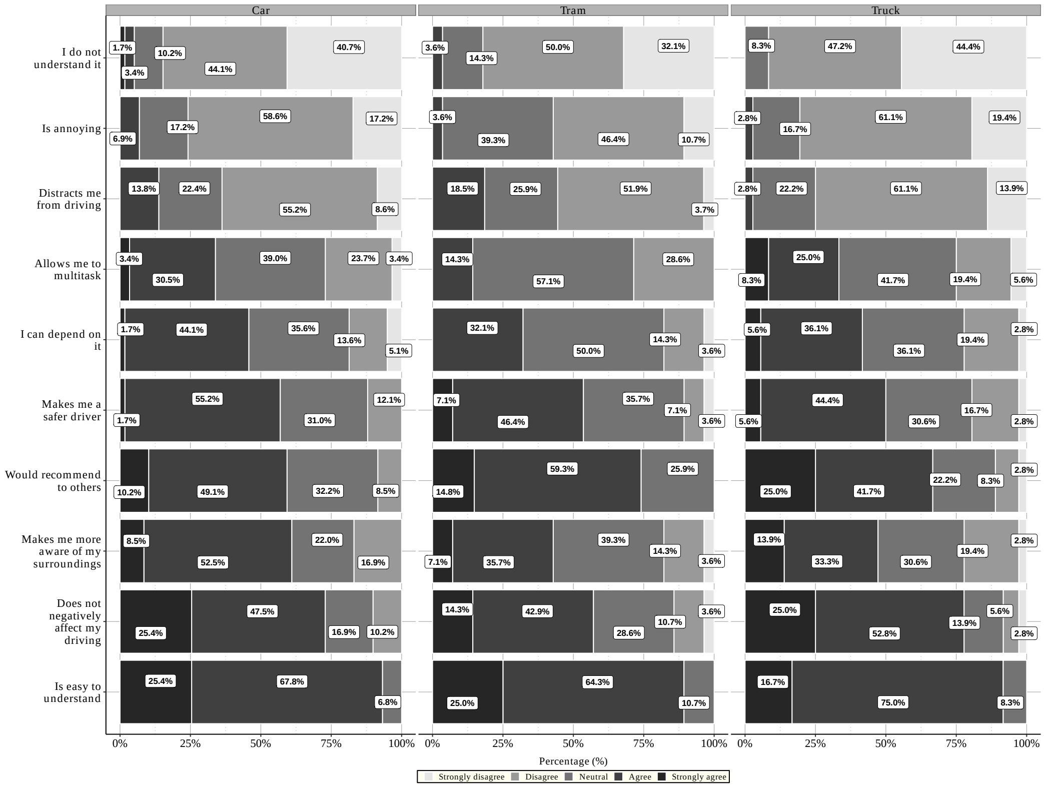

Figure D.11.: Car (N=60), tram (N=28), and truck (N=36) participants' perceptions of the system (part 2)

D.2.3. Log plots

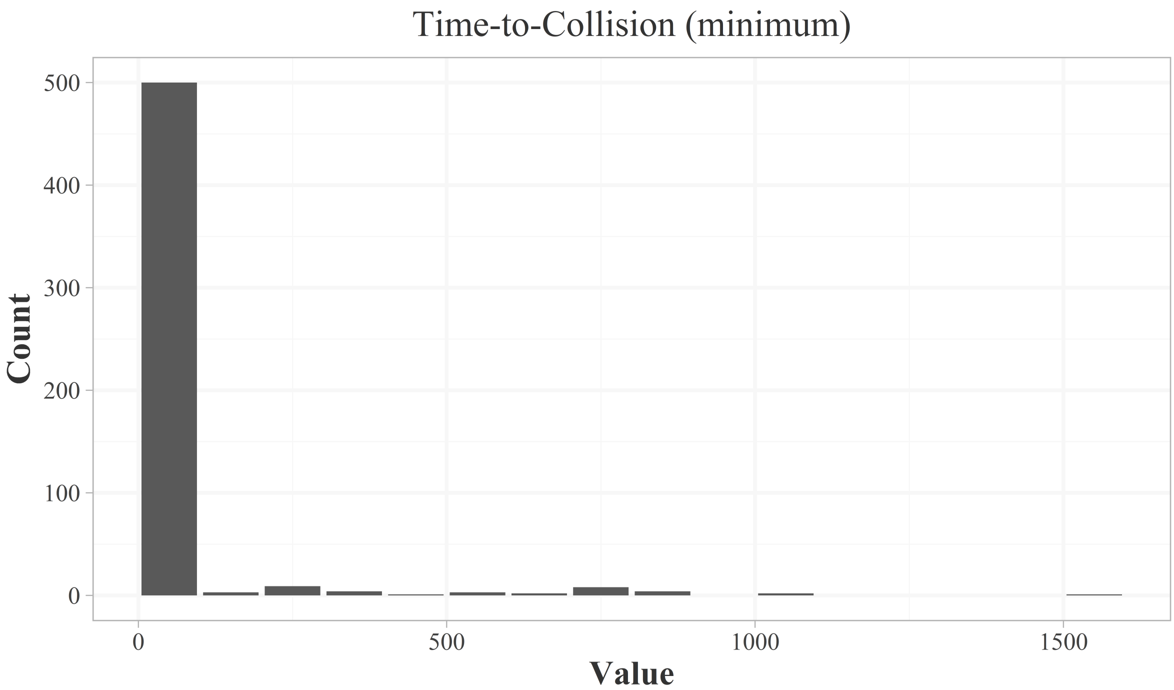

Figure D.12.: Distribution of TTC_{min} in VRU events

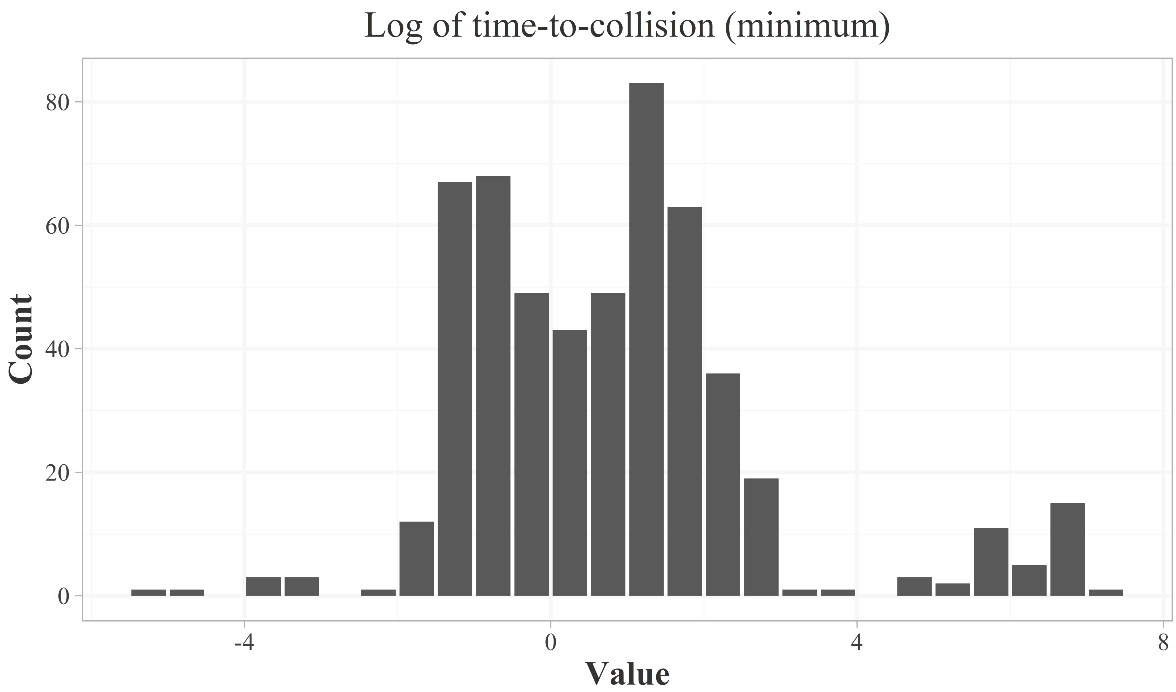

Figure D.13.: Distribution of log(TTC_{min}) in VRU events

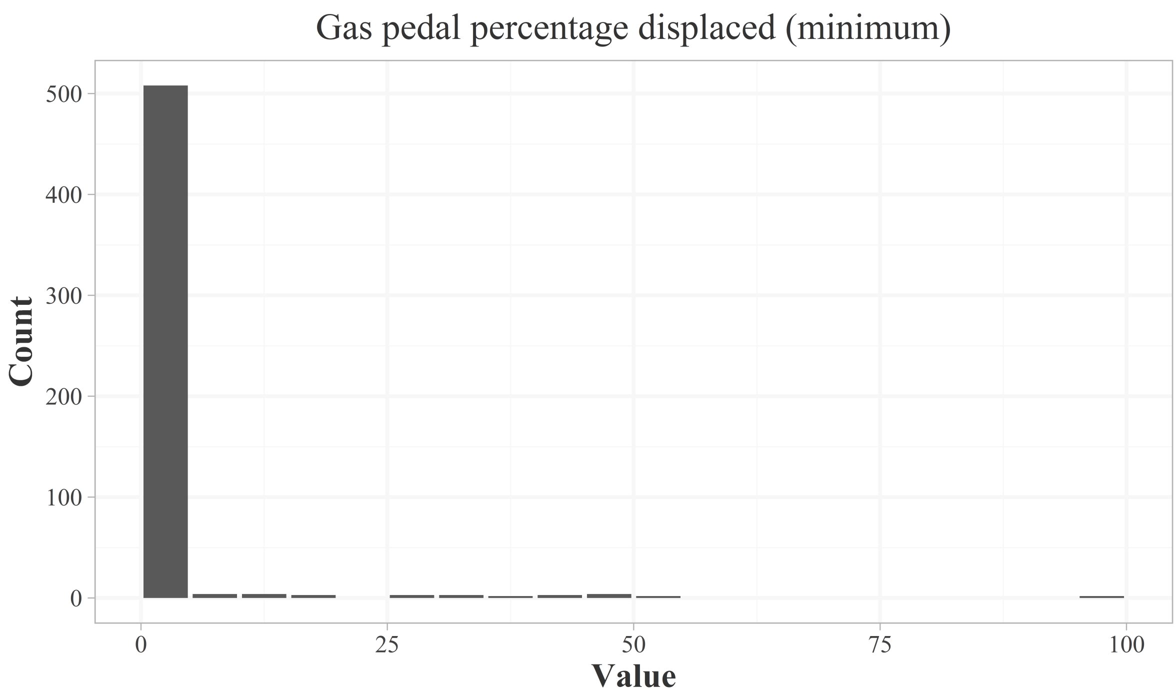

Figure D.14.: Distribution of gas pedal displacement (minimum) in VRU events

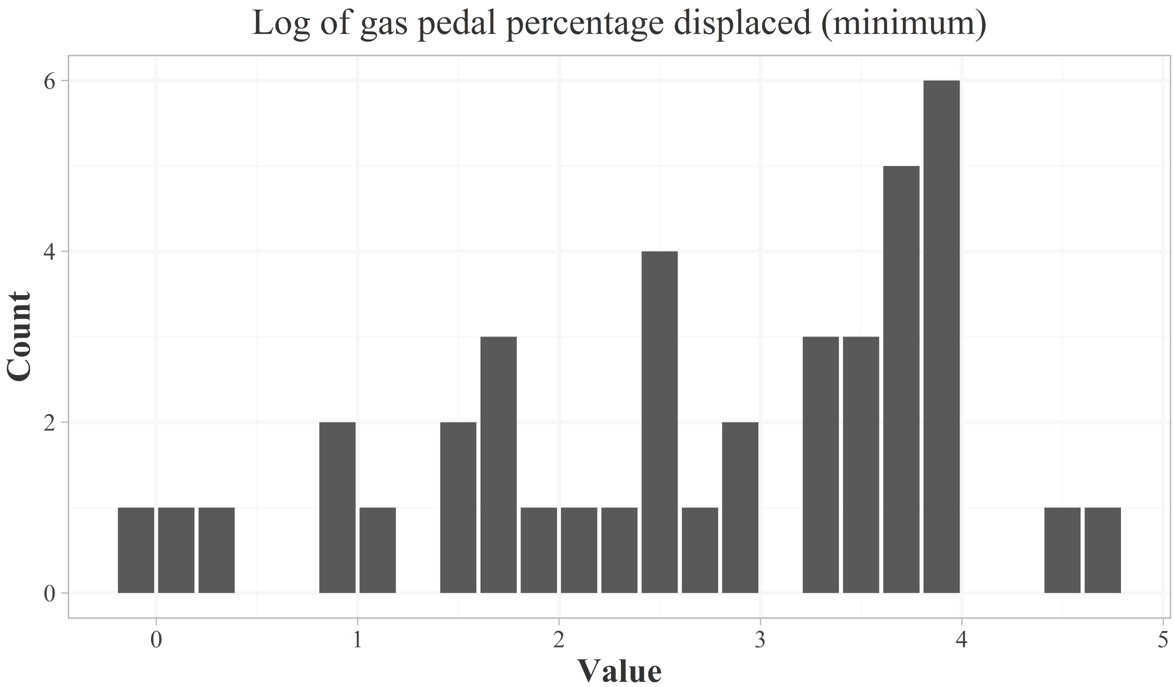

Figure D.15.: Distribution of log of gas pedal displacement (minimum) in VRU events

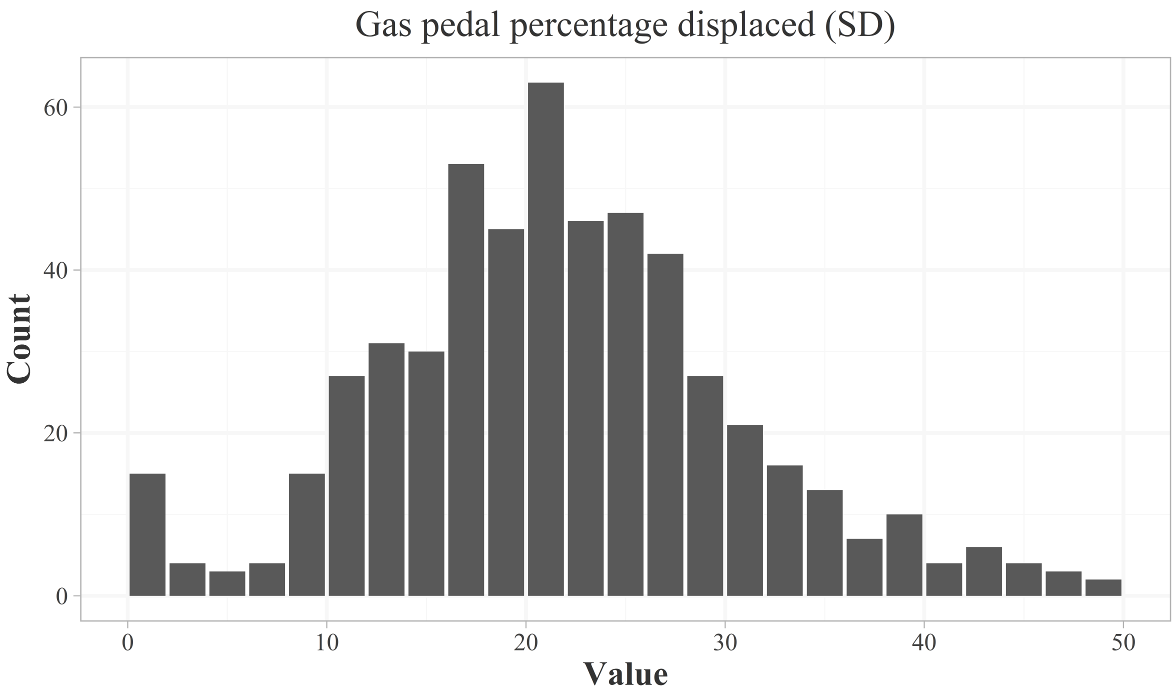

Figure D.16.: Distribution of log of gas pedal displacement (SD) in VRU events

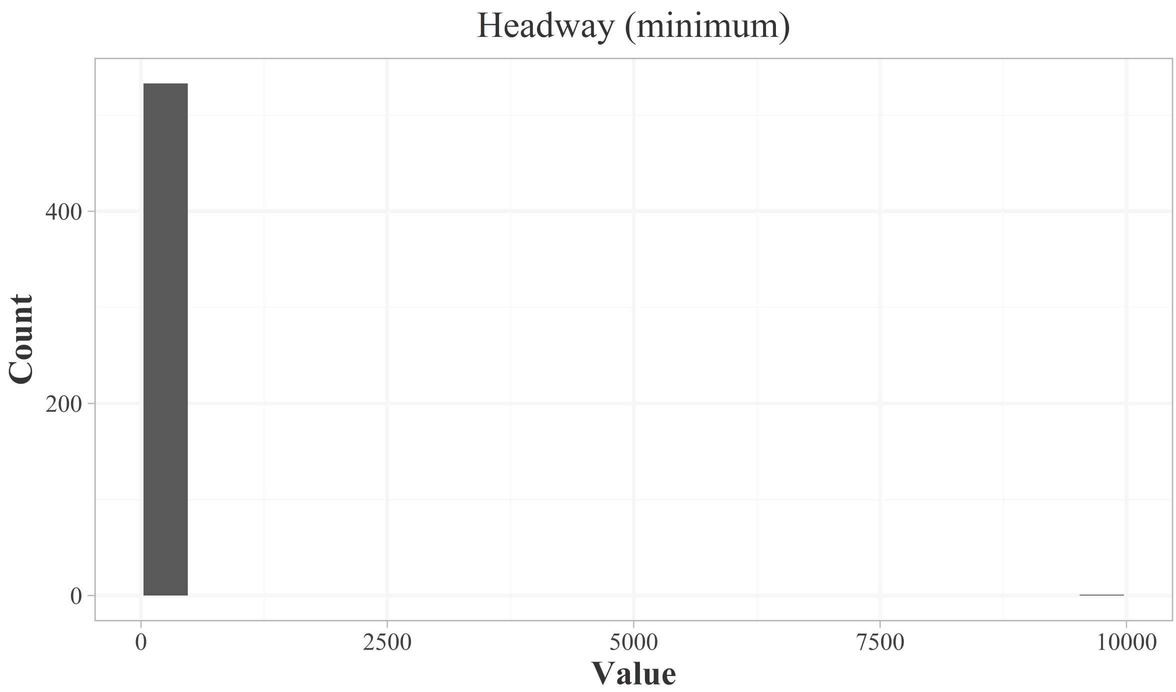

Figure D.17.: Distribution of Headway_{min} in tailgating events

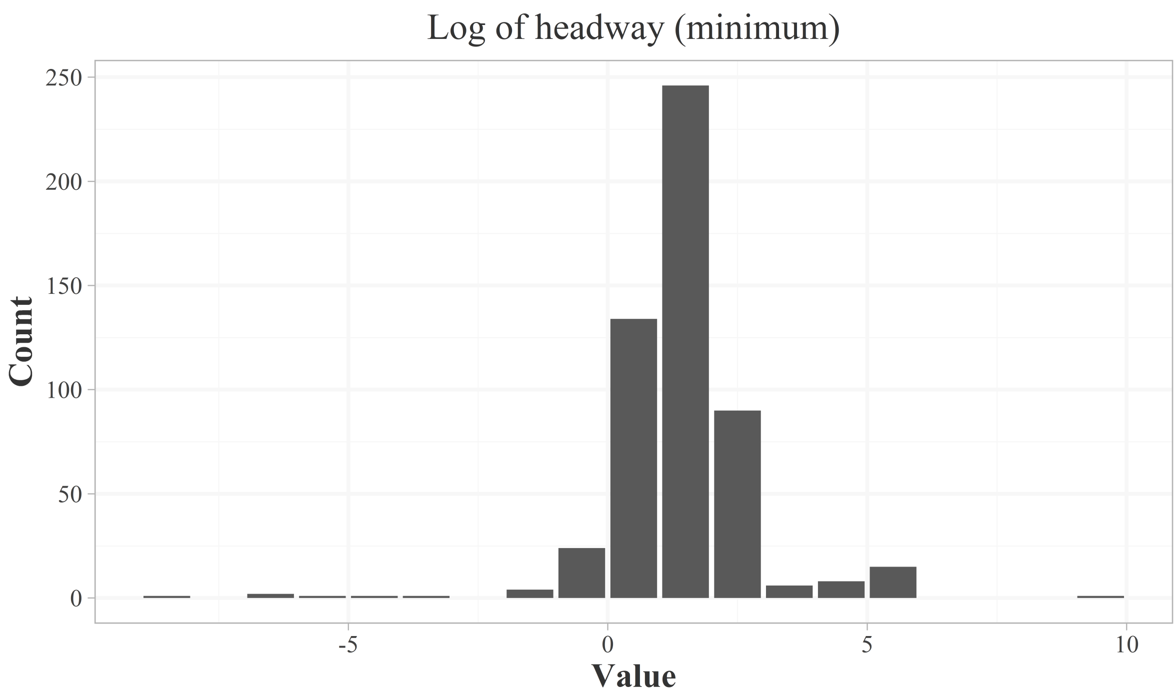

Figure D.18.: Distribution of $\log(\text{Headway}_{min})$ in tailgating events

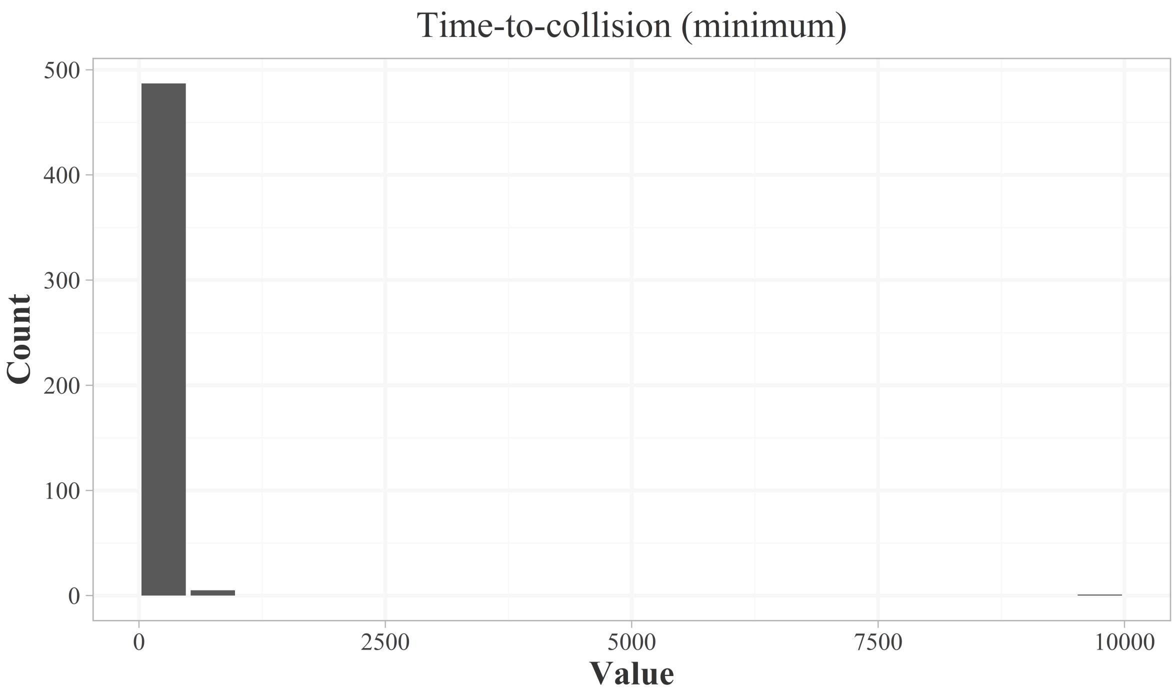

Figure D.19.: Distribution of TTC_{min} in tailgating events

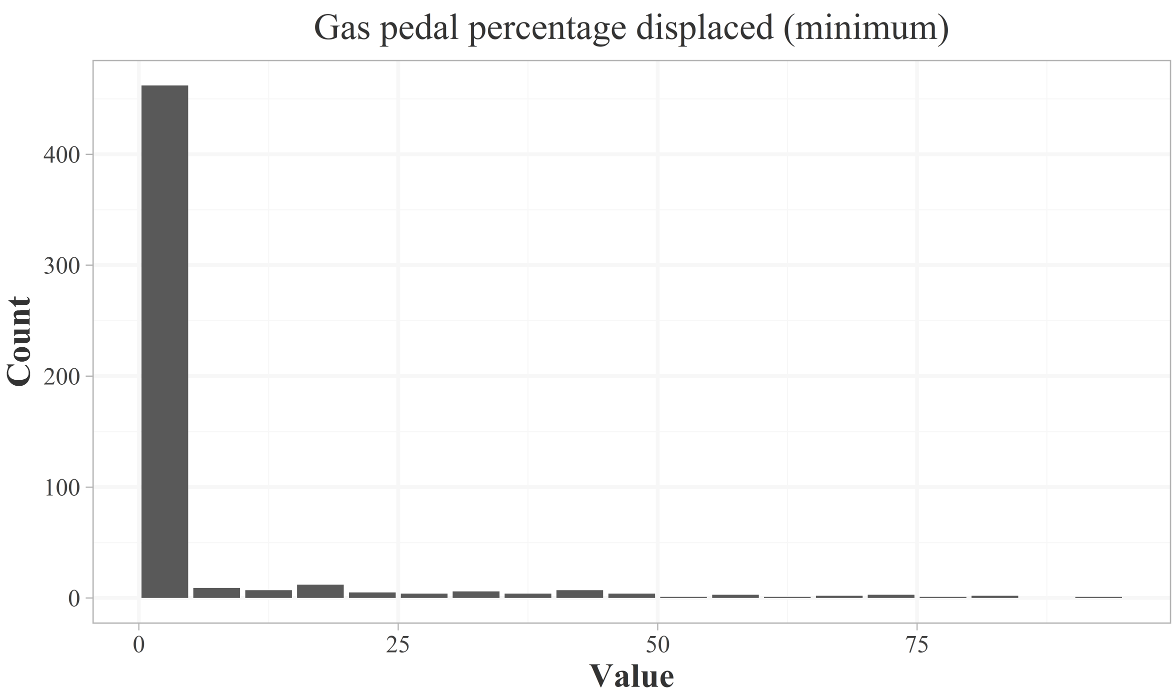

Figure D.20.: Distribution of gas pedal displacement (minimum) in tailgating events

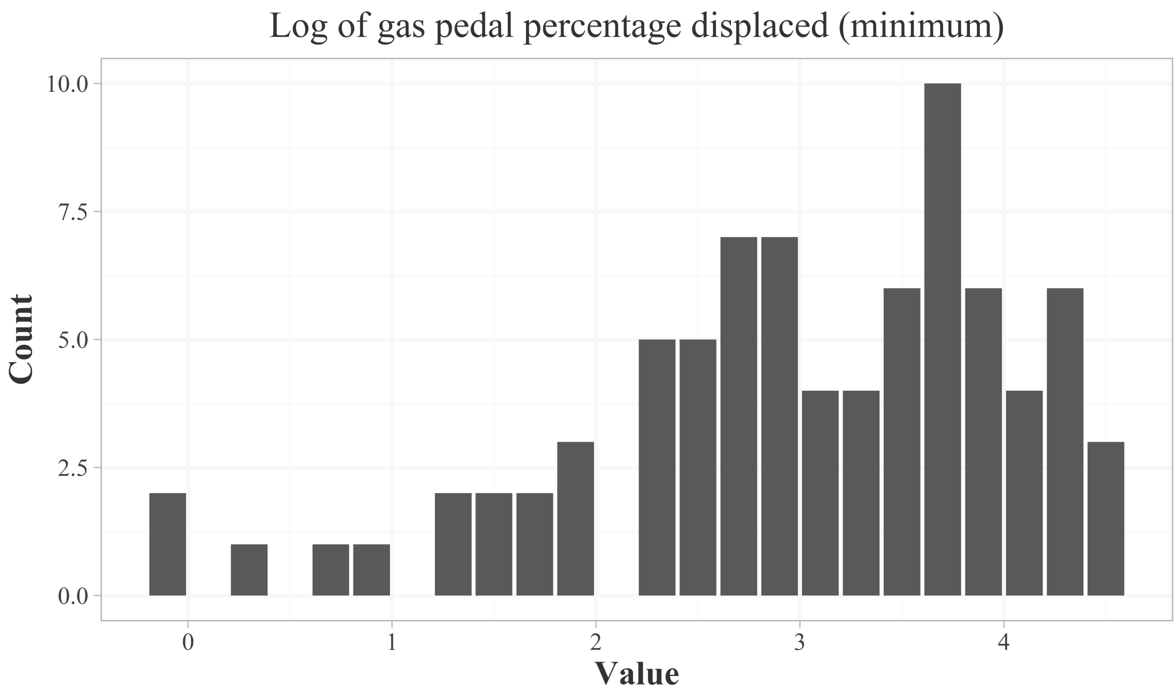

Figure D.21.: Distribution of log of gas pedal displacement (minimum) in tailgating events

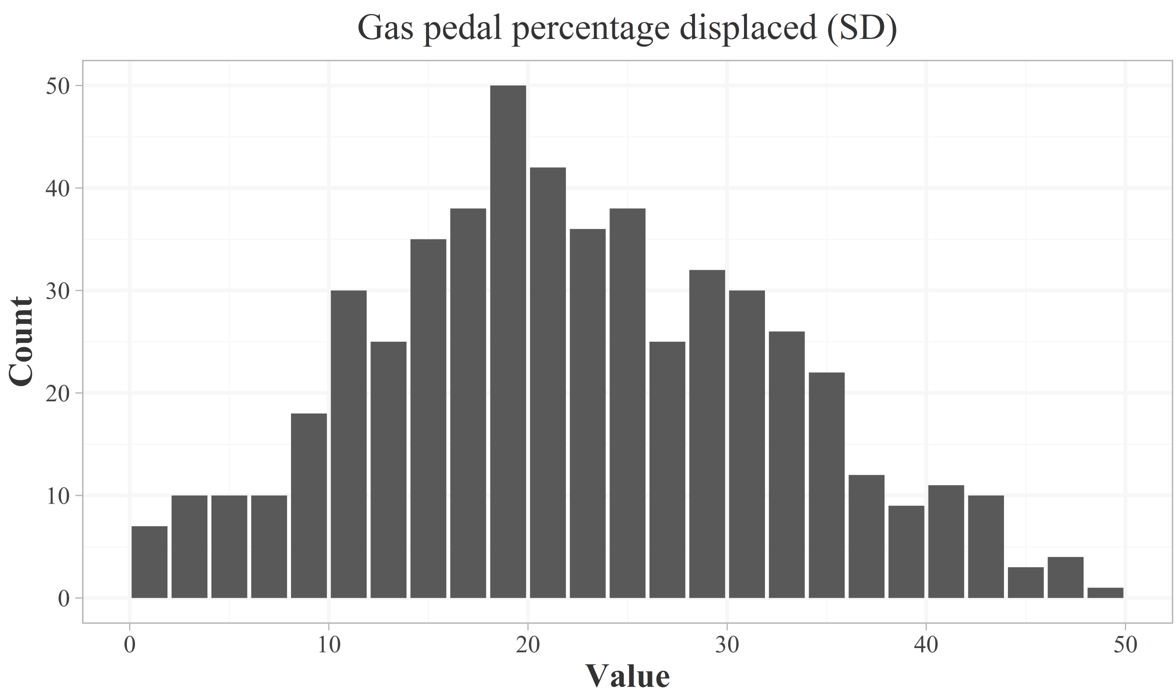

Figure D.22.: Distribution of log of gas pedal displacement (SD) in tailgating events

D.3. Chi-square test results

D.3.1. Car driving simulator study

In the following section, results for chi–square tests are presented for most variables, to see whether there is a significant difference between males and females; these are summarized in Tables D.7 to D.15. Mostly none was noted, with the exception of the highlighted metrics which are significant up to a 95% confidence level.

Table D.7.: Chi–square test results for independence between car participants' ADAS exposure and gender

Variable	'X-squared'	'P-value'
Parking assist	0.939	0.333
Adaptive cruise control	3.72	0.0536
Blind spot warning	2.7	0.101
Forward collision warning	2.04	0.153
Lane keeping assistance	2.36	0.125
High speed alert	3.86	0.0495
Automatic emergency braking	1.15	0.284
Traffic sign recognition	3.23	0.0723
Drowsiness alert	2.44	0.118
Night vision and pedestrian detection	0.122	0.726

Table D.8.: Chi–square test results for independence between car participants' ADAS frequency of use and gender

Variable	'X-squared'	'P-value'
Blind spot warning	1.19	0.756
Traffic sign recognition	1.48	0.688
Automatic emergency braking	3.14	0.37
Parking assist	1.98	0.577
Forward collision warning	4.07	0.254
Lane keeping assistance	2.92	0.404
Drowsiness alert	2.04	0.361
Night vision and pedestrian detection	4.8	0.187
Adaptive cruise control	0.53	0.912
High speed alert	7.2	0.0658

Table D.9.: Chi–square test results for independence between car participants' ADAS perceptions and gender

Variable	'X-squared'	'P-value'
ADAS are useful while driving	0.729	0.695
Using ADAS is a good idea	2.930	0.231
I can maintain safe driving behavior while using ADAS	4.090	0.130
Using ADAS information decreases the accident risk	0.900	0.825
My interaction with ADAS is clear and understandable	2.640	0.267
I trust the information I receive from ADAS	5.070	0.281
I find ADAS easy to use	2.180	0.537
Using ADAS increases my driving performance	0.350	0.950
I will feel more comfortable doing other things (e.g., adjusting the..)	2.260	0.688
Using ADAS information requires increased attention	6.080	0.193
ADAS distract me while driving	2.900	0.407

Table D.10.: Chi–square test results for independence between car participants' distraction engagement when driving and gender

Variable	X-squared	P-value
Adjust in-vehicle devices (e.g., radio, navigation)	6.07	0.108
Converse with passenger(s)	4.00	0.406
Daydream	4.50	0.343
Eating and/or drinking	3.19	0.527
Converse on a hand-held mobile phone	5.78	0.216
Manually interact with a phone	2.39	0.665
Read roadside advertisements	4.18	0.382
Smoke	3.06	0.216
Feel fatigue, stressed, unwell	1.17	0.761

Table D.11.: Chi–square test results for independence between car participants' perceptions of acceptable driving behavior and gender

Variable	'X-squared'	'P-value'
Manually interact with a phone	1.60	0.81
Converse on a hand-held mobile phone	0.12	1.00
Smoke	1.04	0.90
Eating and/or drinking	0.65	0.96
Read roadside advertisements	4.50	0.34
Adjust in-vehicle devices (e.g., radio, navigation)	5.40	0.25
Converse with passenger(s)	2.38	0.67

Table D.12.: Chi–square test results for independence between car participants' perceived ability to drive well (when engaging in certain distracting activities) and gender

Variable	'X-squared'	'P-value'
Manually interact with a phone	4.57	0.207
Converse on a hand-held mobile phone	6	0.199
Smoke	3.58	0.467
Read roadside advertisements	8.21	0.0841
Adjust in-vehicle devices (e.g., radio, É	2.53	0.64
Eating and/or drinking	1.42	0.84
Converse with passenger(s)	2.52	0.642

Table D.13.: Chi–square test results for independence between car participants' perceptions of distracting activities when driving and gender

Variable	'X-squared'	'P-value'
Converse with passenger(s)	2.71	0.61
Adjust in-vehicle devices (e.g., radio)	5.52	0.24
Eating and/or drinking	1.56	0.82
Read roadside advertisements	4.65	0.33
Smoke	1.32	0.86
Converse on a hand-held mobile phone	2.84	0.59
Manually interact with a phone	4.80	0.19

Table D.14.: Chi–square test results for independence between car participants' perceptions of the i–DREAMS system and gender

Variable	'X-squared'	'P-value'
If I use the i-DREAMS system, I will reach my destination safe	4.85	0.18
people who I like would encourage me to use the i-DREAMS system	3.41	0.33
The i-DREAMS system makes driving more interesting.	2.65	0.62
I am afraid that I do not understand the system.	4.28	0.37
I would be proud to show the i-DREAMS system to people	5.32	0.26
I think I can depend on the i-DREAMS system.	0.86	0.93
I think using the i-DREAMS system makes me a safer driver.	1.62	0.65
i-DREAMS system improves my driving performance.	4.24	0.38
I will feel more comfortable doing multitasking with the i-DREAMS	5.32	0.26
While using the i-DREAMS system I can maintain safe driving behavior	3.34	0.34
I would continue to use the i-DREAMS system.	2.56	0.63
Using the i-DREAMS system information requires increased attention	3.99	0.41
I think using the i-DREAMS system makes me more aware of my sure	0.05	1.00
I recommend the i-DREAMS system to other drivers.	3.14	0.37
Using the i-DREAMS system is a good idea.	4.41	0.22
I am confident that the i-DREAMS system does not affect my drive	4.52	0.21
I think the i-DREAMS system is easy to understand.	0.47	0.79
I have the knowledge necessary to use the i-DREAMS system.	4.33	0.23
I think the i-DREAMS system is annoying.	1.19	0.76
The i-DREAMS system distracts me from driving.	3.37	0.34

Table D.15.: Chi–square test results for independence between car participants' perceived clarity of the i–DREAMS system and gender

Variable	'X-squared'	'P-value'
System sound clarity	5.03	0.17
Overall system clarity	2.5	0.475
System visuals clarity	1.27	0.736

D.3.2. Multi–modal driving simulator study

In the following section, results for chi–square tests for testing the impact of modes (cars, trucks, trams) on the i–DREAMS system perception are presented in Table D.16. Based on those results, pairwise Chi–square tests were then conducted for all metrics having a significance higher than 90% (highlighted); the results of these new tests are presented in Table D.17, where highly significant metrics (up to 95%) are highlighted.

Table D.16.: Attitudes towards the i–DREAMS system (between car, trucks, and trams)

Variable	X-squared′	P-value′
Proud to show it to people	21.12	0.007
People would encourage me to use it	20.81	0.008
I know how to use it	17.17	0.028
Improves my driving performance	14.27	0.075
Requires increased attention	13.98	0.082
Makes driving interesting	12.88	0.116
Would continue to use it	10.72	0.218
Is a good idea	10.33	0.243
Helps me reach my destination safely	7.78	0.255
Helps me maintain safe driving	9.68	0.288
Would recommend to others	9.65	0.290
Is annoying	7.20	0.303
Allows me to multitask	8.34	0.401
Distracts me from driving	5.94	0.430
Makes me aware of my surroundings	7.51	0.482
Does not negatively affect my driving performance	6.04	0.643
Makes me a safer driver	5.42	0.712
I can depend on it	5.02	0.755
Is easy to understand	1.49	0.829
I do not understand it	3.64	0.888

Table D.17.: Attitudes towards the i–DREAMS system (significant results between car, trucks, and trams)

Variable	Modes	X-squared′	P-value′
Requires increased attention	Car & Truck	9.58	0.048
Requires increased attention	Car & Tram	4.44	0.350
Requires increased attention	Truck & Tram	3.42	0.491
People would encourage me to use it	Car & Truck	18.75	0.001
People would encourage me to use it	Car & Tram	2.37	0.499
People would encourage me to use it	Truck & Tram	6.47	0.166
Improves my driving performance	Car & Truck	5.91	0.206
Improves my driving performance	Car & Tram	7.97	0.093
Improves my driving performance	Truck & Tram	5.44	0.245
I know how to use it	Car & Truck	2.26	0.521
I know how to use it	Car & Tram	9.88	0.043
I know how to use it	Truck & Tram	9.20	0.056
Proud to show it to people	Car & Truck	15.34	0.004
Proud to show it to people	Car & Tram	8.83	0.065
Proud to show it to people	Truck & Tram	8.87	0.064

D.4. Additional factor analysis results

Table D.18.: Factor analysis results for truck participants' perceptions of ADAS

Loadings	Factor 1	Factor 2
ADAS are useful	0.84	
ADAS reduce accident risks	0.83	
ADAS are a good idea	0.81	
ADAS improve driving performance	0.71	
I can rely on ADAS	0.57	
ADAS are easy to understand		0.82
ADAS are clear and understandable		0.70
ADAS distract me while driving		-0.66
Sum of square of loadings	3.12	2.06
Proportion variance	0.39	0.26
Cumulative variance	0.39	0.65
Factor interpretation	ADAS usefulness	ADAS ease of use

Table D.19.: Factor analysis results for truck participants' perceptions of the i–DREAMS system

Loadings	Factor 1	Factor 2
Persons I like would recommend me to use the system	0.83	
While using the i-DREAMS system, I can maintain safe driving behavior	0.78	
I would be proud to show the i-DREAMS system to people close to me	0.78	
If I use the system, I will reach my destination safely	0.74	
I think I can rely on the system	0.73	
I think the system is annoying	-0.73	
I think by using the system I am a safer driver	0.72	
Using the i-DREAMS system is a good idea	0.69	
The system makes driving more enjoyable	0.67	
Using the system improves my driving performance	0.67	
Using the system makes me more aware of my surroundings	0.63	
The system will not negatively affect my driving performance	0.62	
How clear the i–DREAMS system generally is		0.92
How clear the visuals of the system are		0.60
Sum of square of loadings	6.23	1.74
Proportion variance	0.45	0.13
Cumulative variance	0.45	0.57
Factor interpretation	Perceived usefulness	Perceived ease of use

Table D.20.: Factor analysis results for tram participants' perceptions of the i–DREAMS system

Loadings	Factor 1	Factor 2
While using the i-DREAMS system, I can maintain safe driving behavior	0.77	
I think the i-DREAMS system is annoying	-0.75	
Using the i–DREAMS system makes me more aware of my surroundings	0.71	
The i-DREAMS system makes me a safer driver	0.66	
I think the i-DREAMS system is easy to understand		0.71
I am afraid that I do not understand the system.		-0.60
I would be proud to show the i-DREAMS system to people close to me		0.53
Sum of square of loadings	2.37	1.19
Proportion variance	0.34	0.17
Cumulative variance	0.34	0.51
Factor interpretation	Perceived usefulness	Perceived ease of use

Table D.21.: Factor analysis results for participants' perceptions of the i–DREAMS system (merged car, truck, tram datasets)

Loadings:	Factor 1	Factor 2
Using the system is a good idea	0.72	
I would be proud to show the system to people who are close to me	0.7	
I would recommend the system to other drivers	0.69	
In general, people who I like would encourage me to use the system	0.66	
Using the system improves my driving performance	0.65	
While using the system I can maintain safe driving behaviour	0.64	
Using the i-DREAMS system makes me more aware of my surroundings	0.64	
Using the i-DREAMS system makes me a safer driver	0.63	
If I use the system, I will reach my destination safely	0.63	
The i-DREAMS system makes driving more interesting	0.6	
I think the i-DREAMS system is annoying	-0.51	
I am afraid that I do not understand the system		-0.77
I have the knowledge necessary to use the system		0.69
I think the i-DREAMS system is easy to understand		0.52
Sum of square of loadings	4.58	1.67
Proportion variance	0.33	0.12
Cumulative variance	0.33	0.45
Factor interpretation	Perceived usefulness	Perceived ease of use