THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

A DATA-DRIVEN APPROACH TO SUPPORTING USERS' ADAPTATION TO SMART IN-VEHICLE SYSTEMS

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ABSTRACT

The utilization of data to understand user behavior and support user needs began to develop in areas such as internet services, smartphone apps development, and the gaming industry. This bloom of data-driven services and applications forced OEMs to consider possible solutions for better in-vehicle connectivity. However, digital transformation in the automotive sector presents numerous challenges.

One of those challenges is identifying and establishing the relevant user-related data that will cover current and future needs to help the automotive industry cope with the digital transformation pace. At the same time, this development should not be sporadic, without a clear purpose or vision of how newly-generated data can support engineers to create better systems for drivers. The important issue is to learn how to extract the knowledge from the immense data we possess, and to understand the extent to which this data can be used.

Another challenge is the lack of established approaches towards vehicle data utilization for user-related studies. This area is relatively new to the automotive industry. Despite the positive examples from other fields that demonstrate the potential for data-driven context-aware applications, automotive practices still have gaps in capturing the driving context and driver behavior. This lack of user-related data can partially be explained by the multitasking activities that the driver performs while driving the car and the higher complexity of the automotive context compared to other domains. Thus, more research is needed to explore the capacity of vehicle data to support users in different tasks.

Considering all the interrelations between the driver and in-vehicle system in the defined context of use helps to obtain more comprehensive information and better understand how the system under evaluation can be improved to meet driver needs. Tracking driver behavior with the help of vehicle data may provide developers with quick and reliable user feedback on how drivers are using the system. Compared to vehicle data, the driver's feedback is often incomplete and perception-based since the driver cannot always correlate his behavior to complex processes of vehicle performance or clearly remember the context conditions. Thus, this research aims to demonstrate the ability of vehicle data to support product design and evaluation processes with data-driven automated user insights. This research does not disregard the driver's qualitative input as unimportant but provides insights into how to better combine quantitative and qualitative methods for more effective results.

According to the aim, the research focuses on three main aspects:

- Identifying the extent to which vehicle data can contribute to driver behavior understanding.
- Expanding the concepts for vehicle data utilization to support drivers.
- Developing the methodology for a more effective combination of quantitative (vehicle data-based) and qualitative (based on users' feedback) studies.

Additionally, special consideration is given to describing the drawbacks and limitations, to enhance future data-driven applications.

Keywords: vehicle data, data-driven design, driver behavior assessment, ADAS, Driver Coach approach, real-time driver support.

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Julia Orlovska
Gothenburg, January 2022

APPENDED PUBLICATIONS

The following research publications form the basis for the presented research.

Paper A. Ebel, P., **Orlovska, J.**, Hünemeyer, S., Wickman, C., Vogelsang, A., & Söderberg, R. (2021). Automotive UX design and data-driven development: Narrowing the gap to support practitioners. *Transportation Research Interdisciplinary Perspectives*, *11*.

Paper B. **Orlovska, J.**, Novakazi, F., Wickman, C., & Soderberg, R. (2019, July). Mixed-Method Design for User Behavior Evaluation of Automated Driver Assistance Systems: An Automotive Industry Case. In *Proceedings of the Design Society* (Vol. 1, No. 1, pp. 1803-1812). Cambridge University Press.

Paper C. **Orlovska, J.**, Novakazi, F., Lars-Ola, B., Karlsson, M., Wickman, C., & Söderberg, R. (2020). Effects of the driving context on the usage of Automated Driver Assistance Systems (ADAS)-Naturalistic Driving Study for ADAS evaluation. *Transportation research interdisciplinary perspectives*, *4*, e100093-e100093.

Paper D. Novakazi, F., **Orlovska, J.**, Bligård, L. O., & Wickman, C. (2020). Stepping over the threshold linking understanding and usage of Automated Driver Assistance Systems (ADAS). *Transportation research interdisciplinary perspectives*, *8*, 100252.

Paper E. **Orlovska, J.**, Wickman, C., & Söderberg, R. (2021). Real-time Personalized Driver Support System for Pilot Assist Promotion in Different Traffic Conditions. *Procedia CIRP*, *104*, 26-31.

Paper F. **Orlovska, J.**, Wickman, C., Söderberg, R., Bark, D., Carlsson, C., & Gustavsson, P. (2022). Design and implementation of PA Coach application: a first validation study. Submitted to: *Transportation research interdisciplinary perspectives*, (2022, June 29).

WORK DISTRIBUTION

The work in terms of writing, developing the ideas, collecting the data, analyzing results or producing core findings as well as the reviewing work for every appended paper was distributed among the authors according to the following.

Paper A. Ebel, P. & **Orlovska, J.** were the lead authors of the paper. Empirical data collection and data analysis were equally distributed and performed by Ebel, P and **Orlovska, J.** The method design was developed by **Orlovska, J.**, Ebel, P., and Hünemeyer, S. and corroborated by Wickman C., Vogelsang, A., & Söderberg, R. The results of this paper are produced by Ebel, P. & **Orlovska, J.** and reviewed by Hünemeyer, S., Wickman C., Vogelsang, A., & Söderberg, R.

Paper B. **Orlovska, J.** wrote the paper. The initial idea of the presented method belonged to the author. The method design, as well as the core findings, were formulated by **Orlovska, J.** Novakazi, F. contributed in corroboration of methodology for qualitative evaluation. Wickman, C. and Söderberg, R. provided their feedback and contributed as reviewers.

Paper C. **Orlovska, J.** was the lead author of the paper and Novakazi, F. wrote sections related to the qualitative evaluation. The initial idea of the paper belonged to **Orlovska, J.** The method design was formulated by **Orlovska, J.**, quantitative data collection and data analysis was performed by **Orlovska, J.** Qualitative data collection and data analysis were performed together by **Orlovska, J.** and Novakazi, F., while Novakazi, F. contributed in producing of qualitative findings. Bligård, LO. contributed to conceptualization and reviewing the paper. Karlsson, I.C.M. contributed by structuring and reviewing the paper. Wickman, C. and Söderberg, R. provided their feedback and contributed as reviewers.

Paper D. The initial idea of the paper and method design belonged to **Orlovska J.**, Novakazi, F, and Bligård, LO. Novakazi, F. was the leading author of the paper, while **Orlovska, J.** wrote sections related to the quantitative evaluation and methodology. Quantitative data collection and data analysis were performed by **Orlovska J.** Qualitative data collection and data analysis were performed together by **Orlovska J.** and Novakazi F., whereas Novakazi, F. produced qualitative findings. Bligård LO. and Wickman, C. contributed to the paper's conceptualization, supervision, and reviewing.

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Paper G. **Orlovska, J.**, Wickman, C., & Söderberg, R. (2018). Big data analysis as a new approach for usability attributes evaluation of user interfaces: an automotive industry context. In *DS 92: Proceedings of the DESIGN 2018 15th International Design Conference* (pp. 1651-1662).

Orlovska, J. performed data collection and data analysis, presented the core findings of the paper, and finally wrote the paper. Wickman C. and Söderberg R. contributed with ideas and provided review comments of the full paper.

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Paper L. **Orlovska, J.**, Wickman, C., & Soderberg, R. (2020, May). The use of vehicle data in ADAS development, verification and follow-up on the system. In *Proceedings of the Design Society: DESIGN Conference* (Vol. 1, pp. 2551-2560). Cambridge University Press.

Orlovska, J. wrote the paper. **Orlovska, J.** performed data collection and data analysis. The method design, as well as the core findings, were formulated by the author. Wickman C. and Söderberg R. provided their feedback and contributed as reviewers.

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APPENDICES

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PAPER F Design and Implementation of Driver Coach Application for Pilot Assist: A First Validation Study

LIST OF ABBREVIATIONS AND TERMINOLOGY

ADAS Automated Driver Assistance Systems – built-in vehicle assistance systems that support and facilitate the primary driving task, providing longitudinal and lateral support.

ACC Adaptive Cruise Control – ADAS function providing longitudinal control of the vehicle.

CAN Controller Area Network – CAN bus is a message-based protocol designed to allow the Electronic Control Units (ECUs) found in today's vehicles, as well as other devices, to communicate with each other in a reliable, priority-driven manner. CAN is supported by international standards under ISO 11898.

Context-aware system – system that considers the relevant context to provide the end-user with information and/or services.

DC Drive Cycle – the driving activity that starts when the ignition of the engine turns on and ends when the ignition of the engine turns off.

Driver behavior The set of actions taken by a driver interacting with the system in order to reach a goal or complete a task.

Driver ID User Identification number – few Driver IDs can be connected to one vehicle.

Driving context The summary of external factors that affect driver behavior while using the evaluated system. For the ADAS evaluation, the driving context is defined as the aggregation of traffic, road, and weather conditions that in the association, encourage or discourage the usage of the ADAS.

DRM Design Research Methodology

FlexRay Automotive network communications protocol developed to govern on-board automotive computing. FlexRay is faster and more reliable than CAN, but also more expensive. FlexRay standard is described in a set of ISO standards, ISO 17458-1 to 17458-5.

GPS Global Positioning System – a satellite-based radio navigation system that provides geolocation and time information to a GPS receiver.

GDPR General Data Protection Regulation applied to the processing of personal data and to the free circulation of such data.

HMI	Human-Machine Interaction refers to the communication and interaction between a human and a machine via a user interface.
IoT	Internet of Things – describes physical objects (or groups of objects) with sensors, processing ability, software, and other technologies that connect and exchange data with other devices or systems over the network.
ISO	International Organization for Standardization – an independent, non-governmental, international organization that develops standards to ensure the quality, safety, and efficiency of products, services, and systems.
IVIS	In-vehicle information systems, whether supplied with a vehicle by the manufacturer, or added later by drivers, usually in a form of an app on their mobile devices.
ND study	Refers to a study where a strict experimental design does not constrain the data collection, and where the data are gathered in a natural driving context and under various driving conditions, closely resembling real-driving situations.
ND data	Naturalistic Driving Data – data collected in an ND study.
OEM	Original Equipment Manufacturer
PA	Pilot Assist – ADAS function providing both longitudinal (braking/acceleration) and lateral (steering) control of the vehicle.
Primary Task	Driving the vehicle physically, with mental processing of constantly changing context variables related to the driving.
SAE	Society of Automotive Engineers – a professional international association and standards development organization for the engineering industry, with a focus on automotive, aerospace, and commercial vehicles.
Secondary Task	A task, unrelated to the driving, but requiring the driver's attention away from the driving task. Example: turning on music, setting the navigation, etc.
Smart system	Context-aware systems using sensors and intelligence to describe and analyze a situation and make decisions grounded on the available information in a predictive or adaptive manner, thereby performing smart actions.
UEMs	Usability Evaluation Methods
Usability	The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use (ISO/IEC 9241-11).

UX User Experience – defines as a person's perceptions and responses that result from the use or anticipated use of a product, system or service (ISO 9241-210).

Vehicle data Data collected from vehicle network busses; include driving data, data from vehicle systems, sensors, actuators, software systems, or vehicle apps.

WCU Wireless Communication Unit

WICE Wireless communication and data acquisition system designed for Volvo cars to extract data circulated in vehicle busses.

I

"Data is the new oil – and that's a good thing!"

– *Forbes Technology Council (2019)*

INTRODUCTION

The 4th Industrial Revolution, which encompasses artificial intelligence (AI), information technologies such as Big Data, Internet of Things (IoT), and Cloud services, enhance the exploration of digital possibilities in product development, blurring boundaries between the physical and digital products (Söderberg et al., 2017). Digital transformation encompasses all aspects of product development, from the early stages when data allows predicting different variations in product development, to manufacturing processes where real-time data is used to optimize manufacturing processes (Söderberg et al., 2017). After production, data are actively used for product evaluation and improvements that take place in the new iteration of product development. As a result of this digital transformation, the software industry has grown significantly to meet the increased needs for data processing in various product development tasks.

For users, the rise of the IoT and mobile devices inevitably changes human lives and habits. Everything is now connected or about to be connected, enhancing user expectations regarding new products. Users want to receive the same digital support level, compatibility, and connectivity as in other products they use. Thus digital product development became a new trend to help products to survive in the market. The product development strategy has shifted its interest toward products' digital features or services, indicating a new area of advancement and the grounds for global competition. As a result, an even bigger impact of software-based technologies and data utilization is expected on future products.

However, the process of digital transformation has many challenges. New skills and strategies, and new ways of thinking, are required. Today, blind data collection into massive databases without understanding how these data can be used in all product development stages will not benefit companies. Data requirements should be thoughtfully designed to support the early stages of product research, enable product design and features, and support the product follow-up process by collecting user feedback regarding product use (Ebel et al., 2021). Such an approach will result in data-driven product development that utilizes the data in the design and takes part in iterative verification and validation processes of design features, resulting in a better customer experience of the product.

Compared to other domains, the automotive industry will experience an even more comprehensive digital transformation due to the multi-system structure of its end products. Today, information technology already forms a significant part of a car, transforming vehicles from purely mechanical into mobile computing units on wheels (Tornell et al., 2015). Hundreds of sensors support the performance of these systems to enable in-vehicle connectivity, provide new functionality, and automate existing features (Orlovska, 2020). In the near future, the fields of smart and connected services will continue influencing the future car concept – alongside electric mobility and automated driving (Winkelhake, 2019). In-vehicle systems will become increasingly more intelligent, eventually taking full responsibility for systems and functions in the car, following individual driver preferences (Römer et al., 2016; Gao et al., 2016).

Advanced Driver Assistance Systems (ADAS), which is the focus of this research, are good examples of advanced vehicle systems that provide automation to the primary driving task. ADAS are built-in vehicle support systems that provide longitudinal control of a vehicle through accelerating or braking in various traffic conditions, and/or lateral control through providing steering assistance (Naranjo et al., 2003). The main purpose of ADAS is to support and facilitate primary driver activities, providing assistance in real-time driving. The development of systems like ADAS has changed the nature of driver activities. Nowadays, the driver is cooperating with different automated functions offered by the vehicle. This cooperation presumes a good understanding of the system and the functions it provides. However, the systems are not fully automated, which means that they have limitations and cannot provide the correct support in all driving conditions. The driver is ultimately responsible for monitoring whether the system, with the existing limits, can operate under particular driving conditions. This supervisory role can be demanding for the driver if she/he does not fully understand how the system works.

Unfortunately, some of the previously conducted research shows that a significant percentage of drivers do not fully understand the limitations of driving support systems (Llaneras, 2006). A wrong understanding of the system's limitations creates misconceptions between the driver and the system. In many cases, drivers expect the system to be able to handle on-road situations when the system activation preconditions are not fulfilled. Moreover, the level of automation can differ between two systems in the same vehicle, which means that the driver can misinterpret the system capabilities and not engage when the system requires intervention from the driver. The study conducted by Jenness et al. (2008), demonstrated that drivers' expectations regarding the system capabilities were higher than the actual capabilities of system performance. Consequently, these types of misinterpretations of the ADAS capabilities damage driver's trust and reliance on technology (Itoh, 2012; Kazi et al., 2007) and may decrease technology use and acceptance. Therefore, for any automotive OEM that invests in the development cost of a new system, a deep understanding, and interpretation of driver needs and behavior regarding the use of ADAS is required in order to reflect on and improve the systems to meet users' expectations.

The improvement of data feasibility that comes with the development of sensors-based smart technologies brings new abilities for vehicle systems design and evaluation. Any vehicle today generates a large amount of data from sensors that enable the performance of ADAS functionalities. The same sensors can potentially provide user-related data on driver performance (Orlovska, 2020). Analysis of this data can contribute to a better understanding of interactions between driver and system. Moreover, the ability of vehicle data to identify the driving event and assess the driving conditions in the moment of driver-system interaction can add to the context-awareness of this evaluation. As a result, engineers can have data-informed feedback on drivers' behavior that automatically captures how users interact with ADAS, when they use it, and how they understand the system. This knowledge can be further used to design personalized support for each user to motivate the improvement of their behavior, raising the efficiency of system use. Motivating drivers to use automation more effectively can be seen as a coaching process. If this motivation happens in real-time, drivers can improve their skills and adopt new use strategies that could be further developed into new habits.

1.1 DEFINING THE PROBLEM

The utilization of signal data to understand user behavior and support user needs began to develop in sectors such as internet services (Angelini, M. et al., 2018; Carta, T. et al., 2011), smartphone apps development (Visuri, A. et al., 2017), the gaming industry (Kim J.N. et al., 2008) amongst others. This bloom of data-driven services and applications forced OEMs to consider possible solutions for better in-vehicle connectivity. However, digital transformation in the automotive sector is highly challenging. Most automotive software platforms were initially designed with a limited ability to obtain user-related vehicle data. And today, the high complexity of a vehicle makes this transformation too costly and slow compared to other industries.

Nevertheless, the digital transformation in the automotive sector is ongoing. One of the challenges is identifying and establishing the relevant user-related data that will cover current and future needs, helping the automotive industry to cope with the pace of digital transformation. At the same time, this development should not be sporadic without a clear purpose or vision of how newly generated data can support engineers in creating better systems for drivers. The important factor is to learn how to extract the knowledge from the immense data we possess and understand the extent to which this data can be used.

Another issue is the lack of established approaches regarding vehicle data utilization for user-related studies. This area is relatively new to the automotive industry. Despite the positive examples from other fields that demonstrate the potential for data-driven context-aware applications, automotive practices still have gaps in capturing driving context and driver behavior. This lack of user-related data can partially be explained by the multitasking activities that the driver performs while driving the car and the higher complexity of the automotive context compared to other domains. Thus, more research is needed to explore the capability of vehicle data to support users in different tasks.

1.2 RESEARCH FOCUS

Considering all interrelations between the driver and in-vehicle system in the defined context of use helps to obtain more comprehensive information and better understand how the system under evaluation can be improved to meet driver needs. Tracking driver behavior with the help of vehicle data may provide developers with quick and reliable user feedback on how drivers are using the system. Compared to vehicle data, the driver's feedback is often incomplete and perception-based since the driver cannot always correlate his behavior to complex processes of vehicle performance or clearly remember the context conditions. Thus, this research aims to demonstrate the ability of vehicle data to support product design and evaluation processes with data-driven automated user insights. This research does not disregard the driver's qualitative input as unimportant but provides insights into how to better combine quantitative and qualitative methods for more effective results.

According to the aim, the research focuses on three main aspects:

- Identifying the extent to which vehicle data can contribute to driver behavior understanding.
- Expanding the concepts for vehicle data utilization to support drivers.

- Developing the methodology for a more effective combination of quantitative (vehicle data-based) and qualitative (based on users' feedback) studies.

Additionally, special consideration is given to structuring, developing, and improving the feasibility of vehicle data. Hence, additional focus is given to describing the drawbacks and limitations with the view to enhancing future data-driven applications.

1.2.1 Scientific goals

From the academic point of view, vehicle data utilization is a reasonably new area, with the ongoing development of methods for logging, processing, analysis, and visualization of interaction data (Visuri A. et al., 2017; Vuillemot R. et al., 2016). The scientific goal of this research is to develop a theoretical framework for the efficient use of vehicle data that allows driver behavior to be taken into account when evaluating or designing intelligent automotive systems.

Specific research is also addressed to develop a methodology for incorporating newly generated data-driven knowledge in the existing methods for user behavior evaluation, and into the decision-making processes. Today, there is no single method that helps to capture the complexity of user behavior. Therefore, the research should be focused on the effective combination of existing methods for user behavior evaluation. The academic acknowledgment of such methodology is needed. Thus, the scientific goal of this research is to design methods for effective user behavior evaluation utilizing vehicle data, and to study how to incorporate these methods into the existing methodologies for user behavior evaluation.

1.2.2 Industrial goals

This research project has been carried out in close collaboration with Volvo Cars. The project's overall purpose is to learn how to utilize vehicle signals at the company level to understand and support driver behavior for advanced in-vehicle support systems. Thus, the industrial goal for this research is to define the scope where the vehicle data contributes to the understanding of user behavior, since results solely based on vehicle data cannot uncover all aspects of driver behavior. In this step, the validation of obtaining results is one of the primary industrial goals. Subsequently, this type of data-driven evaluation can contribute to understanding the system's implications, advantages, and limitations from a user's point of view.

To achieve this goal, the following company resources need to be further explored: (i) the technical feasibility of vehicle data and their limitations; (ii) the possibilities for further development of user-related data; (iii) the means and methods for data acquisition, data processing, and data storage. The above-described actions will help build a robust infrastructure for data support at the company level. The ultimate goal is to contribute to practical solutions for the efficient collection, processing, and use of vehicle data, participate in the development of user-related data signals, and drive the improvement of vehicle sensors and data acquisition systems.

Another goal of this research is to understand users' perceptions regarding data-driven services. In particular, if drivers are ready to share personal data with the automotive OEMs to receive advanced support, and whether they perceive active support during the driving activity as valuable and safe, since safety aspects related to driver distraction during primary driving are fundamental.

1.2.3 Research questions and hypotheses

This research is based on set hypothesis that the proper specification of vehicle data and consequent processing and analysis of these data will support better understanding of user interaction between the driver and the In-Vehicle Information System (IVIS). Based on this hypothesis, the author also assumed it is possible to perform in-depth driver behavior evaluation based solely on vehicle data, considering the three-fold interrelations between the driver, the system, and the context of interactions. As a result of the set hypothesis and assumption, two following research questions were identified:

RQ 1: What vehicle data are relevant to support the understanding of driver behavior?

Thousands of vehicle signals from numerous sensors, actuators, and built-in applications are circulated in the vehicle and are available today. It is essential to identify the appropriate data points contributing to driver behavior assessment for a particular system or set of systems. Thus, this research question relates to what factors are essential for driver behavior evaluation, how the interactions between the driver and the system happen, and what data represent the context of these interactions. Furthermore, this question relates to automotive OEMs' limitations regarding the data and their utilization in various evaluation types, and the possibilities to override these limitations.

RQ 2: How can the data-driven approach be incorporated into existing methods for driver behavior evaluation?

Today, there is no systematic approach regarding vehicle data utilization for driver behavior evaluation. Traditionally, qualitative methods were adopted and broadly used for human behavior understanding. Nowadays, with the advantages of the data-driven approach becoming more evident, there is a question of how traditional evaluation can benefit from data-driven insights and how combining qualitative and quantitative methods can enrich the overall understanding of driver behavior.

Subsequently, when conducted studies proved the ability of data-driven user behavior evaluation, a new hypothesis was set. This time the hypothesis related to the utilization of vehicle data for real-time support of driving activities. The author thought that real-time vehicle data processing to understand driver behavior can help develop a personalized recommendation system to improve driver adaptation to in-vehicle systems. As a result of this hypothesis, another research question was set:

RQ 3: How can vehicle data be used to support users' adaptation to smart in-vehicle systems?

This research question relates to the feasibility of data-driven driver support that happens in real-time and aims to provide personalized support, tailored to each driver in the form of active coaching during driving activity. This research question presumes the proposal of a novel way (for the automotive sector) of data-driven utilization for active coaching and exploring the challenges throughout its implementation.

1.3 RESEARCH SCOPE

Operating a vehicle is a complex and multi-tasking activity. A driver performs vehicle controls on the road, gets support and information from multiple in-vehicle systems and functions, and interacts with the external environment. Current technologies do not allow us to track and understand the complete driver behavior for all in-vehicle systems. To limit the driver behavior evaluation scope to a manageable level, this research focused on the driver behavior assessment of two ADAS functions, namely Adaptive Cruise Control (ACC) and Pilot Assist (PA).

Although ACC and PA provide lateral and/or longitudinal support, they are semi-automated systems. This means that these systems leave the driver in full control and with the responsibility for the driving task. According to the Society of Automotive Engineers (SAE) classification (SAE standard J3016, 2018), six levels of driving automation are defined, ranging from level 0 (complete manual driving) to level 5 (fully autonomous driving). Figure 1 provides a detailed description of the driving automation levels.

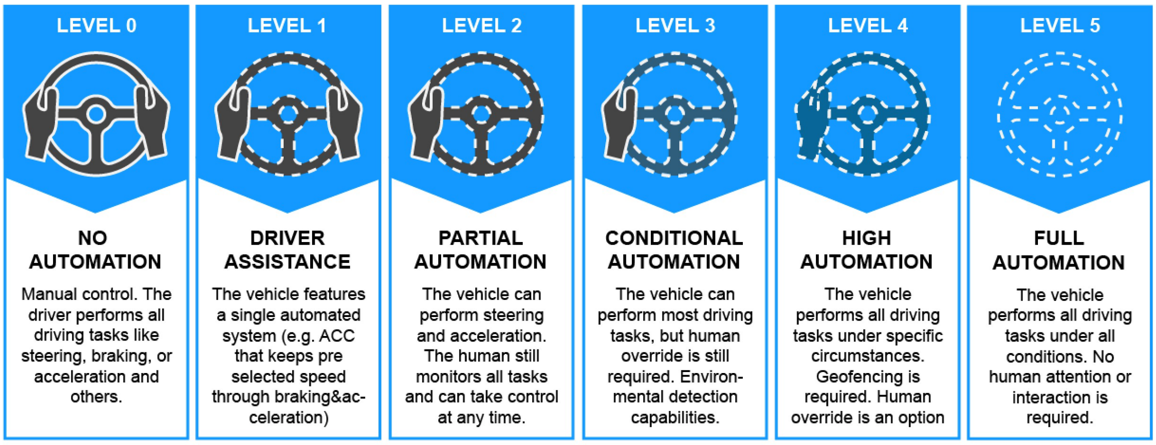

Figure 1. Levels of driving automation (SAE standard J3016).

According to the SAE classification, ACC is defined as a Level 1, *Driver Assistance* system. ACC is designed to be a supplementary driving aid and is not intended to replace the driver's attention and judgment. PA is classified as a Level 2, *Partial Automation* system. Level 2 of the SAE classification means that the driver has full responsibility for the driving task even though the system can provide braking and acceleration support together with steering assistance. The driver has to monitor the driving environment and be prepared to take back control of the system at any time.

Distinct levels of driving automation expect a different level of driver involvement in ADAS performance, starting from full control over the ADAS performance and ending up with zero interaction with the system. These levels of driver involvement have a significant effect on driver behavior. Since ACC and PA are classified as Level 1 and Level 2, respectively, driver behavior in this research is a specific behavior connected to Levels 1-2 of automation. On these Levels, the driver has full responsibility for the driving activity, and a high level of interactions with the function since both the assistance of Level 1 and the automation of Level 2 are very limited. Thus, the results of studies conducted in the frame of this research cannot be applied to the same systems with a higher or lower level of automation.

Furthermore, this research is based on ADAS functions and data from one automotive company. Even though most car manufacturers offer ADAS functions today, the author investigated only ADAS functions designed by a single OEM in this research. The author chose two functions, namely ACC and PA, since they were the most advanced yet not well-studied functions in their usage and user reaction to them.

Altogether, this research is grounded on the utilization of vehicle data. CAN (Controller Area Network) and FlexRay busses, and built-in GPS tracker are the primary sources in this research. Due to the subjective nature of driver behavior, many naturalistic driving studies try to capture personal driver data by including the use of advanced technologies, such as eye-tracking, reading biological data, and measuring the driver's psychosomatic parameters. These types of data were not collected in this research since it aimed to design for the complete vehicle fleet. This means that these types of personal data cannot be used due to legal limitations regarding the generation and processing of sensitive data, as well as the complicated and expensive equipment that must be added to the vehicle's configuration. Moreover, the complexity of such a dataset would increase the volume of data collected significantly without providing any benefits for the data analysis since the outcomes and meanings of the video stream or eye-tracking data are often dubious and need additional verification by the use of questionnaires (Köhler et al., 2015).

Considering the above, this research's primary focus is the design of simple and reliable solutions that enable data-driven design and evaluation without additional instrumentation or problems related to General Data Protection Regulations (GDPR). In the future perspective, this will allow the application of this research results to all vehicles entering the market.

1.4 OUTLINE OF THE THESIS

The rest of this thesis is structured as follows. First, we present an overview of related research in Chapter 2. Chapter 3 presents the approach adopted for this research. Chapter 4 presents the core findings from the papers appended to this thesis. Chapter 5 is dedicated to discussing the results in connection to the research questions. Chapter 6 presents the results and the research challenges identified. This chapter also discusses further developments and possible improvements related to the results presented in this thesis.

2

FRAME OF REFERENCE

This chapter provides an overview of the research area to familiarize the reader with the existing terminology, approaches, and methods used within the automotive systems development arena.

There are several noticeable studies focused on identifying the main elements that build an ecosystem for any in-vehicle system development and evaluation (Barbé & Boy, 2008; Harvey et al., 2011; Orlovska et al., 2020). According to Harvey et al. (2011), to successfully design, evaluate and predict the performance of in-vehicle systems, a comprehensive understanding of the task, user, and system is required. Orlovska et al. (2020) underlined the importance of the context consideration in driver-system interrelations analysis. The study of Barbé & Boy (2008) presents the framework describing five main elements that comprise automotive system development and evaluation: namely the driver, the vehicle, the system, the environment, and the driving task. In this thesis, the author adopts the vision of Barbé & Boy (2008) to all the elements of the interaction (see Figure 2).

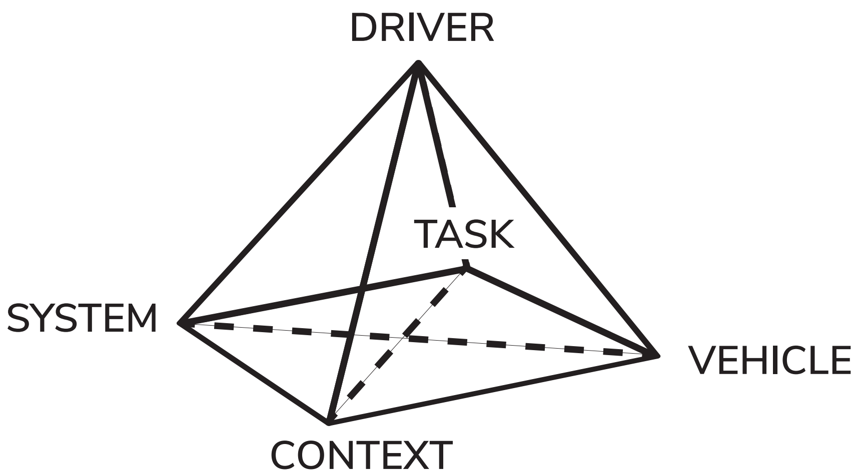

Figure 2. Main elements of driver-system interaction in automotive sector (Modified from Barbé & Boy, 2008).

The following sections define and explore these key elements and present the related work on intelligent systems development within and outside the automotive sector.

2.1 VEHICLE SYSTEMS

The definitions of vehicle systems spread out from general automotive systems to information and automated systems. Since the focus of this work is to explore driver behavior, general systems that build the core of any vehicle and support the primary functions of a car (e.g., the engine, fuel system, ignition system, electrical system, and other systems) are not the focus of this study. Instead, this research focuses on driver behavior with vehicle information and semi-automated systems, since they depend on the dynamically changing context and are designed to keep a driver in the interaction loop, which is essential for driver behavior assessment.

2.1.1 Vehicle Information Systems

Vehicle Information Systems (Vehicle IS) are socio-technical systems that imply the human-machine interaction between driver (or any other authorized user, e.g., vehicle owner, co-driver or passengers) and vehicle. Vehicle IS back the user with both context- and task-related information. The information is typically supported by the ability of hardware and software to process digitalized input efficiently. Kaiser et al. (2018) defines Vehicle IS as a *"... software applications processing vehicle data and/or other relevant data from different sources to finally provide valuable and action-relevant information to the vehicle driver and/or to other stakeholders"*. Thus, the primary goal of any Vehicle IS to support the driver's decision-making process by creating value with the information retrieved from a set of interrelated components and helping drivers to improve performance efficiency, increase safety, or better understand the processes in the car. To achieve this goal, Vehicle IS must be designed with a clear understanding of what could bring value for a driver. Since Vehicle IS are often connected to secondary task performance, the biggest challenge is to balance the information provided to the driver with the driver's distraction from the primary driving task.

A Vehicle IS can provide information to its users throughout different vehicle operation phases: before, during, or after the trip is completed. Based on the needs of the vehicle operation phase, Vehicle IS can be placed inside the car and then be called In-Vehicle Information System or IVIS. Otherwise, Vehicle IS can be portable, such as an app on a smartphone or e-mail based statistics (Banski & Faenger, 2017). An IVIS often has a built-in interface and may therefore directly use the dashboard or an additionally instrumented screen to provide real-time support to its users. In contrast, portable Vehicle IS usually move its interface to mobile devices such as smartphones or pads that can work through physical or wireless connections (Ryder et al., 2017). Due to mobile devices' connectivity with the car, portable Vehicle IS can support users through all vehicle operation phases and can be used before, during, and after driving. Figure 3 provides a visualization of two Vehicle IS in three operation phases (adapted from Kaiser et al., 2018).

Type	Examples of Vehicle IS		
Built-in	Optimization hints	Live visualization	Behavior statistics
Portable	Routing suggestions	Driver coaching	Road statistics

Figure 3. Vehicle IS in different operation phases.

2.1.2 In-Vehicle Automation Systems

The research community further distinguishes a group of in-vehicle automation systems from Vehicle IS (Kaiser et al., 2018). The reason for this is the focus of in-vehicle automation systems on excluding a driver from the activity loop and eliminating information flow regarding the automated task. An example of in-vehicle automation systems could be *active safety systems* (e.g., Anti-Lock Braking Systems (ABS) or Electronic Stability Control (ESC)) and *Advanced Driver Assistance Systems* (ADAS) represented today by many functions, such as Lane Change Assist (LCA), Lane Keeping Assistant (LKA), Intelligent Speed Adaption (ISA), Adaptive Cruise Control (ACC), Driving automation systems (e.g., Volvo Pilot Assist).

ADAS are designed to support the driving task. They are mostly semi-automated systems that provide longitudinal control of a vehicle through accelerating or braking in various traffic conditions, and/or lateral control through providing steering assistance (Ziebinski et al., 2017). Functions such as ACC and Volvo PA represent well this group of systems on the automotive market. With the help of vehicle cameras and a radar system, ACC provides longitudinal control of a vehicle through accelerating or braking, according to pre-set speed and time interval to the vehicle in front. PA offers the same functionalities as ACC, as well as steering assistance, helping to keep the vehicle in its lane at the set speed and preselected time interval to the vehicle in front, as long as there are clear markings on the road. Thus, the PA delivers both longitudinal and lateral control of a vehicle (Volvo Cars, 2022). Although ACC and PA provide lateral and/or longitudinal support, they are semi-automated systems. This means that they leave the driver in full control and with the responsibility for the driving task.

Three organizations, namely the Society of Automotive Engineers (SAE, 2014), the United States National Highway Traffic Safety Administration (NHTSA, 2013), and German Federal Highway Research Institute BASt (Gasser & Westhoff, 2012), have independently formulated definitions that classify automated driving systems, from driver assistance to full automation. Although the definitions of SAE, NHTSA, and BASt differ, the criteria used by these organizations to classify levels of automation are similar (SAE, 2014). The most important criteria are how the three primary driving tasks (i.e., lateral control, longitudinal control, and monitoring) are distributed between the driver and the automated system. Therefore, in this research, we adopted the SAE classification (see Figure 1) that defined six levels of driving automation, ranging from level 0 (complete manual driving) to level 5 (fully autonomous driving).

Even though PA offers lateral and longitudinal support, it leaves the driver in complete control and with full responsibility for the driving task. According to the manufacturer, the functions ACC and PA cannot cover all driving situations, traffic, weather, and/or road conditions. Moreover, PA requires clear markings on the road in order to function. The manufacturer further states that PA is not recommended to be used in demanding driving conditions, such as city driving or other heavy traffic situations, in slippery conditions, when there is a great deal of water or slush on the road, during heavy rain or snow, during poor visibility, on winding roads, or on highway ramps (Volvo Cars, 2021). The described limitations show that PA cannot operate in specific driving conditions. This means that the ability of the driver to understand and recognize these limitations while driving becomes critically important.

Similar to PA, many ADAS remain at early levels of driving automation, meaning that a driver has full responsibility to control the performance of these systems. Hence, the information flow could increase rather than decrease since a driver should get information regarding both system behavior (to identify the critical moments when the system cannot support fully) and the usual informational support on maintaining the factual interaction with the system. Therefore, according to the author's understanding, ADAS remains a part of the in-vehicle information systems, since ADAS users might need even more information flow than regular Vehicle IS that lack automation.

2.1.3 Vehicle data

Almost every automotive system today is powered by data. The number of in-vehicle systems in one car is much higher than in most other products. Hence, the volumes of data needed to support vehicle performance are excessively high. Moreover, the continuously growing connectivity trend dictated by other industries brings in new customer demands for always-on in-vehicle connectivity (Tornell et al., 2015), which results in supporting IoT, ubiquitous computing, and generating a new set of data to provide connected services. Nowadays, automotive OEMs generate enormous amounts of data in volume, with high velocity, in real-time, to support the development of automated processes and ensure the performance of Vehicle IS.

According to Kaiser et al. (2018), Vehicle IS can be understood as a software systems processing relevant data from different sources to provide valuable and action-relevant information to the vehicle driver or other people in the car. To describe the transformation of vehicle data into useful information, the data value chain proposed by Curry et al. (2016) can be applied. Figure 4 describes the vehicle data value chain processes, from data generation to information utilization.

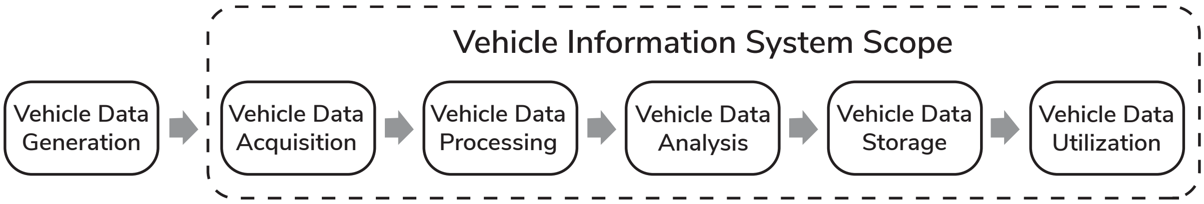

Figure 4. Vehicle data value chain (Curry et al., 2016).

Alongside the system performance support, the vehicle data analysis gives us the possibility of context-aware user behavior evaluation and indicates how well the user understands the system functionality. Vehicle data also offers the ability to determine certain trends in user behavior, as well as identify specific use errors, the usage of a particular function, and other usability issues (Orlovska et al., 2020). Additionally, the ongoing research on the quality of vehicle data and its applicability has a positive effect on the feasibility of this data, which has been gradually improving over recent years.

Hence, if data are one of the key sources for Vehicle IS, then data analytics is the key to maximizing its value. The data generated by modern Vehicle IS are usually integrated from multiple data sources, are of enormous size, have high complexity, and are represented by low-level signals that, without additional computation, cannot be easily interpreted by humans in raw form. Therefore, the data should first be transformed into meaningful pieces of information (Kaiser et al., 2018) and then outputted to the driver in the form of driving metrics (e.g., fuel consumption). Another way of using data is to use data bits as input to a statistical model that will generate new insights with the help of advanced methods. For example, the "driver distraction" metric cannot be directly captured and understood. The statistical model for "driver distraction" identification would include complex relations of various driver behavior indicators and their consistency over time. Machine learning algorithms are often used to "train" data in the statistical model and calculate properties of data that are related to the parameter(s) of interest.

Besides direct vehicle data, Vehicle IS can utilize cloud data, data from mobile devices, and/or connected services. Even driver behavior data could be part of the Vehicle IS computations formulas. However, when data from humans are utilized, GDPR legislation must be applied, protecting data exploitation for other purposes. The process of data sharing is often connected to driver trust. Driver consent is easier to acquire for built-in IVIS designed by automotive OEMs, often due to the driver's confidence in the OEM or their desire to enable intelligent in-vehicle functionalities. The external Vehicle IS often have problems with driver consent; low trust in the developers, the risk of private data leaking, and the use of these data for different purposes often hinder the acceptance and dissemination of these systems.

In contrast, In-Vehicle Automation Systems mainly utilize vehicle data as a faster and more reliable data source. In-Vehicle Automation Systems are mostly performance-related rather than behavior-related since they normally process and analyze live performance information without saving the data for retrospective use.

2.1.4 External data acquisition systems

In the R&D area, access to direct vehicle data is usually limited due to data protection policies applied by automotive OEMs. To test their concepts and models, researchers, both in academia and industry, have to refer to external acquisition systems to obtain the required data. This creates a number of drawbacks compared to direct vehicle data processing. These drawbacks will be further described in the following sections.

Nevertheless, these external acquisition systems are developing in parallel with the improvement of the automotive platforms and represent intermediate solutions to support the current needs for data-driven evaluation. Today, to achieve the required data collection, an external wireless communication and data acquisition unit needs to be installed in all test vehicles. It enables the management of the data from the vehicle fleet by keeping track of map-based positioning, mileage, uptime, and diagnostic codes. In this research, we used the WICE external data acquisition system to retrieve and process the data. The WICE system is an external wireless communication and data acquisition unit that requires installation in the test vehicle. It supports the testing and validation stages of automotive development by efficient use of telematics technology and global coverage (Johanson, 2017). The WICE system consists of two major parts: (i) Wireless Communication Unit (WCU) – the hardware unit that supports communication interfaces for data logging and measuring, including telematics services (types of logged data include CAN bus and FlexRay bus, analog inputs, digital inputs, USB and Ethernet data); (ii) Back-end server infrastructure includes the web-based front-end user interface, including data storage units and database with meta-information.

Overall, the system provides metrology services from connected vehicles, including a collection of measurement data signals of various types (logs, signals, images, video, etc.). The WICE system can manage vehicle fleet information by keeping track of map-based positioning, mileage, uptime, Diagnostic Trouble Codes, etc. Figure 5 shows the high-level architecture for WICE data logging and the real-time data processing system.

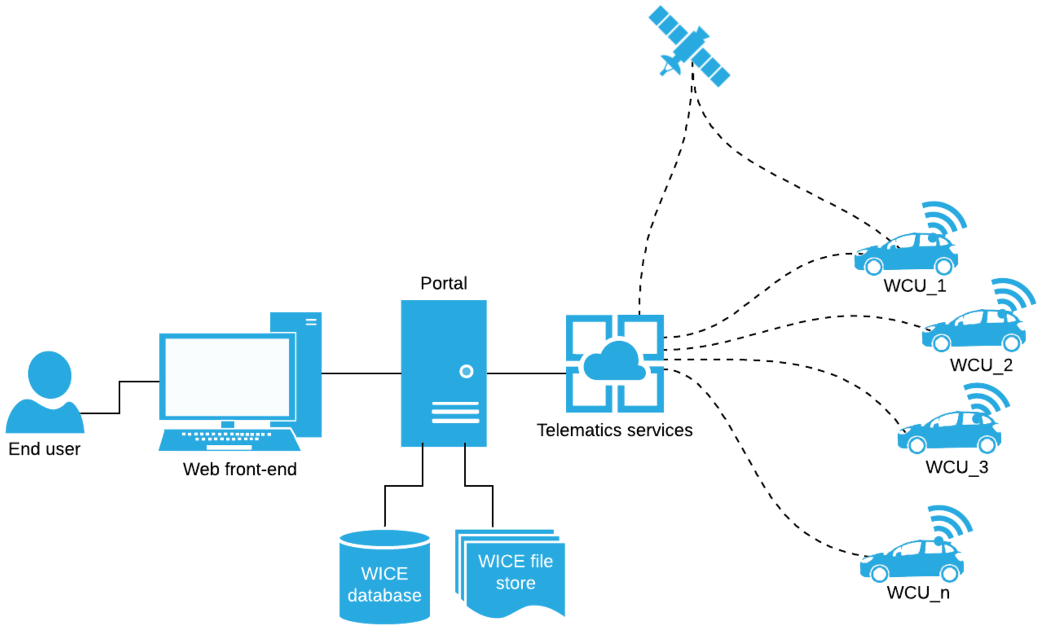

Figure 5. A high-level overview of the WICE-system communication infrastructure.

The WICE portal is a complex software providing server-side functionality for vehicle testing, verification, and development. The WICE users interact with the system through the web front-end that gives users access to the WICE application services and data. The WICE portal implements the core functionality of the supported services, including fleet management of connected vehicles, tasks and data management, user management, as well as administration. The telematic services provide the communication interface to the connected vehicles. Every connected vehicle has a WCU installed in the car. The WCU hardware unit contains monitoring and diagnostics modules and enables in-vehicle data capture, including GPS positioning and vehicle status information. The state of the WICE system is kept in the WICE database. The measurement data logged from vehicles is stored in the WICE file store, large volume storage based on the data lake concept.

However, this approach has its limitations. To provide the required data, every vehicle needs to be additionally instrumented with an external acquisition system. This does not allow the OEM to expand the study to the whole vehicle fleet of real users. The OEM's employees who use instrumented vehicles and share the data might cause a bias, being often far more experienced in using support systems due to their work tasks and engineering backgrounds.

Moreover, currently, no systematic approach regarding the use of vehicle sensors data has been developed, and vehicle data are not used to full capacity. While vehicle data are extensively used for system performance verification, they are less used for driver performance evaluation and driving context assessment. Therefore, this research project can be of benefit to engineers, enabling them to further develop the tools and methods for more effective ways of data collection, data processing, and data applicability.

2.2 TASK

Driving is a complex, multitasking activity (Regan et al., 2009). It consists of interactions between the driver, the car, and the environment (Rakotonirainy & Tay, 2004). A driver performs many different tasks while continuously monitoring the dynamically changing driving conditions. However, not all performing tasks are equally important. The automotive context distinguishes two types of tasks: primary (supporting the driver with driving activity) and secondary (supporting the driver with additional comfort and information).

Primary driving tasks
A driver's primary goal is always to operate the vehicle safely (Lansdown, 2000), following all road and traffic regulations. Thus, primary driving tasks involve maintaining safe longitudinal and lateral positions and detecting and responding to hazard situations while navigating a route (Seppelt & Wickens, 2003). Tasks supporting longitudinal control are accelerating, braking, choosing the speed, and keeping a safe distance between cars, while tasks supporting lateral control of the vehicle refer to steering, lane choice, and maneuvering (Hedlund et al., 2006). Further, the situation assessment involves the following tasks: monitoring the roadway, checking the mirrors, and checking the dashboard displays (Mitchell, 2009; Angell et al., 2013).

Secondary (non-driving-related) tasks
Hedlund et al. (2006) defined secondary tasks as the range of tasks performed by the driver and not related to driving. Secondary tasks aim to enhance the driving experience while addressing the driver's needs (Engström et al., 2004). Secondary functions provide information about the trip and the vehicle in the form of traffic information or navigation that support driver decisions (Seppelt & Wickens, 2003). Additionally, secondary functions aim to enhance driver comfort by providing entertainment (e.g., radio, MP3 or TV/DVD), communication means, climate control, seat/wheel warming, to name just a few.

Handley (2021) introduced a model where he summarized the knowledge on primary and secondary tasks to a specified level of detail, pointing out relevant interfaces or actuators (see Figure 6).

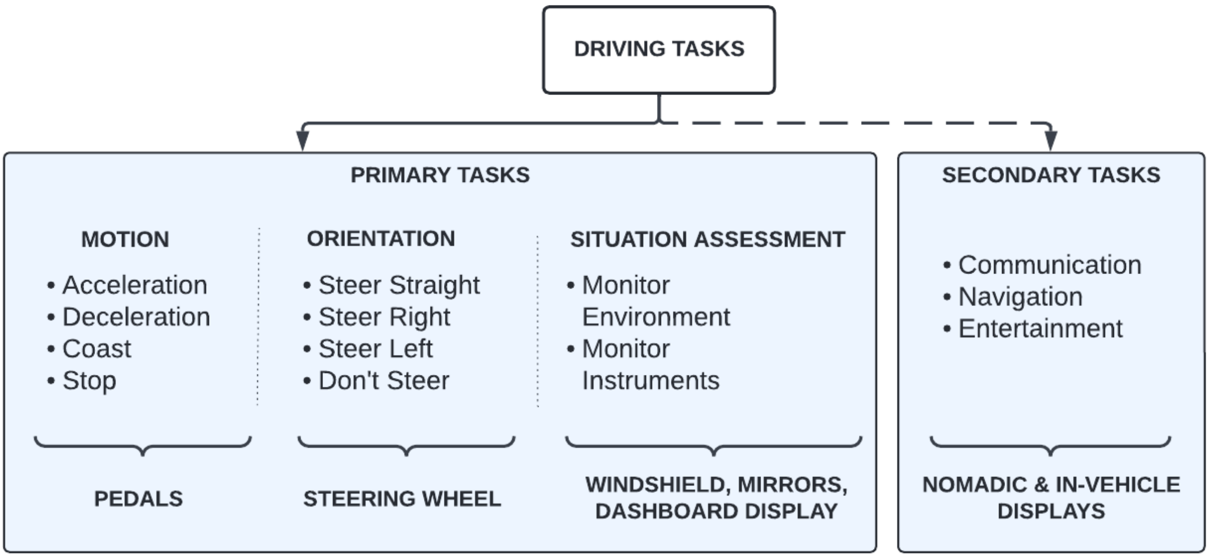

Figure 6. Driving tasks description model (Handley, 2021).

Since ADAS, according to its definition, supports primary driving tasks, automating one or a few driving tasks, this thesis is concerned about the driver's interaction with primary driving tasks. At the same time, the Driver Coach application, designed as a proof of concept in this thesis, provides informational support and, therefore, is part of the secondary tasks for a driver.

2.3 WHAT IS CONTEXT?

Context plays a central role in the development of any intelligent system. The early notion of context was mainly concerned with the time and place of a particular event. Since then, increased data availability and technical advances have allowed for more complex context representation, including information about a person, system, and interacting environment.

The most cited definition of context is by Dey (2001), who defines context as *"... any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves."*

Winograd (2001) had a different view on the context, criticizing Dey for being too broad on the context description. According to him, *"Something is context because of the way it is used in interpretation, not due to its inherent properties"*. If there is no action by the user or computer whose interpretation depends on the particular parameter, then it is just a part of the environment, not the context.

Dourish (2001) explained the differences in defining context by different research approaches, from Positivist and Phenomenological research theories. Positivist theories strive to reduce social phenomena to simplified models that capture underlying patterns. According to the Positivist theory, the context can be described regardless of the actions taken. Therefore, Dey's definition is consistent with this view. In contrast to Positivist, Phenomenological theories say that the world, as we perceive it, is a result of interpretations. Therefore, context arises from the activity and cannot be described on its own.

In this thesis, the author adopts a Phenomenological approach, claiming that defining the scope of the context should be performed with reference to the designed system, its application domain, and usage environment. According to this approach, two different car systems will most likely have a distinct usage context, despite the common description in the car environment. The usage context will consist of a tailor-made description of variables taking part in the context interpretation by our logic.

Later work, focusing on further defining context, recognizes different types of contexts and introduces categories of context. Thus, Zimmermann (2007) derived five main context characteristics, namely: individuality, activity, location, time, and relations. Soylu et al. (2009), in their survey, went even further, introducing device, application, information, and historical contexts, breaking them down into subcategories such as internal/external (for user), hardware/software (for the system), hardware/software (for device context) and other. This indicates the necessity of defining the context for each smart system individually, depending on its complexity, purposes, interacting space, and ways the interaction with a user is organized.

2.3.1 Driving context

One more context classification needs to be derived in the automotive sector, namely the driving context. The vehicle's system is continuously operating under conditions to which it must adapt. These conditions arise due to external factors, both static and dynamic. Static context factors are mostly related to road infrastructure. The dynamic characteristics are related to the traffic density, weather conditions, and other unforeseen events, such as accidents, road works, pedestrians, or other non-static road participants and objects that have an unpredictable effect on driving.

According to Zhai et al.'s (2018) definition, driving context summarizes external factors that affect driver behavior while using the evaluated system. However, in the context of smart automated systems like ADAS, both a user and the system itself could react to the driving context change due to the development of automated solutions for reading driving context (Orlovska et al., 2020).

Thus, for systems like ADAS, the driving context could be defined as the aggregation of traffic, road, and weather conditions that affect the ADAS performance and/or driver performance, encouraging or discouraging ADAS use. Moreover, as for any other type of context, the description of the driving context is not something predetermined or enduring. Since context is system dependent, it should be derived on a case-by-case basis.

2.3.2 Context-aware systems

The concept of context-awareness refers to both Vehicle IS and in-vehicle automation systems that consider the relevant context to provide end-users with information and/or services. According to Dey et al. (2001), the context is used to present information and services to users, ensure system performance, and tag context to information for later retrieval. Thus, context-awareness can be defined as adaptiveness to changing circumstances and responsiveness, according to the context of use. Context can refer to real-world characteristics, such as temperature, time, or location. The user can update this information manually, or the system can retrieve contextual data from sensors, connected devices, or applications. Some examples of context-aware services could be real-time traffic information or real-time route updates for a vehicle user.

While the definition for the context-aware system is relatively simple, practical implementation, according to Satyanarayanan (2001), brings many challenges and issues for consideration (see Figure 7).

Implementing a context-aware system requires many issues to be addressed. For example:

- How is context represented internally? How is this information combined with the system and application state? Where is context stored? Does it reside locally, in the network, or both? What are the relevant data structures and algorithms?
- How frequently does context information have to be consulted? What is the overhead of taking context into account? What techniques can one use to keep this overhead low?
- What are the minimal services an environment needs to provide to make context-awareness feasible? What are reasonable fallback positions if an environment does not provide such services? Is historical context useful?
- What are the relative merits of different location-sensing technologies? Under what circumstances should one be used in preference to another? Should location information be treated just like any other context information, or should it be handled differently?

Figure 7. Issues in context awareness (Satyanarayanan, 2001).

Thus, the design of context-aware systems is not a trivial task. Wei & Chan (2007) specify four major areas where Satyanarayanan's questions could be placed: *defining the context*, *acquiring the context*, *modeling the context*, and *adapting to contextual information*. When we talk about how to determine the context, it is important to understand that context is system specific. It consists of any information that needs to be utilized to model an adequate context model that ensures the complete understanding of the user and system reasonings. System-specific context means that the context of one system may make no sense to the other (Wei & Chan, 2007), even if we talk about two similar systems in the same car or two applications in a mobile phone.

Context acquisition implies the collection of environmental information defined as a context. This is usually done through physical sensors, social (media) sensing, and the output from other systems or services that play a role in system reasoning or user interpretation of the situation. The context acquisition could consist of direct and indirect signals. Direct low-level signals could represent pieces of the context by themselves. For example, activating the fog lights in the car describes visibility on the road. Indirect low-level signals are collected to obtain a meaningful context understanding by learning the event based on several indirect parameters that do not represent something significant by itself. As an example, driver distraction identification could be used. No signal represents the driver's distraction by itself. Usually, researchers create modules where different behavioral parameters are collected and analyzed in combination. This cumulative analysis of the driver's behavior data helps reasoning regarding driver distraction in a particular moment or situation. In such cases, pre-processing of signals data is required, followed by segmentation, classification, or feature extraction to obtain a meaningful understanding of one piece of context. Moreover, a data fusion concept is often a part of context acquisition, since integrating multiple data sources for the same target often produces more accurate and verified information than that provided by any individual data source.

Context modeling refers to a signal-based representation of the real part of an environment relevant to the context-aware system. The main requirements set for data modeling are an adequate and accurate representation of the context and flexibility of its structure for further handling. Thus, Wei & Chan (2007) highlight the importance of *data structure*, *integrity*, and *manipulation* for context modeling, emphasizing the representation, structure, and organization of contextual data and its relations. According to them, an adequate data structure facilitates exchanging context information inside and between smart systems and simplifies the processes related to context information storage, validation, modification, retrieval, and reasoning. Integrity in context modeling refers to validating both the structure completeness and the ability of context information to represent the real context, since a highly dynamic context often leads to its ambiguity. Manipulation defines the set of operators that can be applied to the data structure, including context reasoning. Data structure and the data integrity of a context model affect the context manipulation abilities.

Adapting to context is the main principle for context-aware systems that refers us back to the context-aware system's definition. A context-aware system reacts to a context change and provides its services considering this change. Therefore, the most important factor at this point will be to decide what should be affected by the context change, how to adapt user behavior to contextual changes, and when is the appropriate time for these adaptations. For example, the most advanced context adaptation takes place in the system's run time so that the user adaptation happens in real-time. All these questions about what, how and when, related to context reasoning, should be designed for each system individually and be precisely described in the logic.

2.3.3 Smart systems

Smart systems incorporate a context-aware vision of the situation using sensors and intelligence to describe and analyze a situation and make decisions grounded on the available information in a predictive or adaptive manner, thereby performing smart actions. Usually, the system's intelligence refers to an autonomous operation based on closed-loop control and networking capabilities.

Although the research community struggles to develop a universal definition of smart systems (Romero et al., 2020), and most research for smart systems development is domain-dependent, there are several commonalities that any smart system should have. Smart or Intelligent systems commonly incorporate diverse components, such as (1) sensors and other means for signal acquisition, (2) technologies transmitting the information to the control unit, (3) control and decision units that give instructions based on the available information, (4) components conveying decisions and instructions, and (5) enablers that trigger the required action.

A study by Romero et al. (2020) defined eight main characteristics inherent in any smart system:

- *Communication capability* (ability to exchange data, communicate system capabilities, and inform about the environment)
- *Embedded knowledge* (ability to capture relevant knowledge related to an understanding of users or interacting environment, and consider this knowledge in the decision-making process)
- *Learning ability* (the ability of advanced methods and algorithms to autonomously modify the knowledge of the system, enabling an adaptive behavior and allowing the adequate handling of new contexts or situations)
- *Reasoning* (the ability of advanced computing techniques to provide strategic decision-making, predict future states of the environment, or provide flexible data processing)
- *Perception capability* (the ability of the smart system to continuously sense or perceive the environment and themselves, describing and analyzing the environment using data acquired by the sensors)
- *Control ability* (the ability of the smart system to perform specific tasks, initiate user intervention to perform these tasks, or make autonomous decisions, depending on the system's capabilities and the level of its automation)
- *Self-organization* (the ability of the smart system to independently adapt its own structure and organize the system elements while keeping its original objectives)
- *Context-awareness* (the ability to sense, interpret and consider the state of the environment, relevant to the smart system)

Based on the above characteristics, a system could be considered smart if it can create and update its internal knowledge, enabling communication between its elements, reasoning, and optimizing its decisions by sensing and interpreting the environment.

There are multiple examples of smart and context-aware systems development. The rise of the IoT and mobile devices boosted the growth of smart services that support human lives and habits in different areas. The pioneering areas for context consideration have become location-based applications and services (Chen & Kotz, 2000), such as call forwarding applications (Want et al., 1992; Bennett et al., 1994), Cyberguide, a mobile location-and history-based tourist guide (Abowd et al., 1997), Personal shop assistance (Asthana et al., 1994) and other applications, according to the review of Chen & Kotz (2000).

Later, the development of smart features expanded to broader spheres. The smart home concept became one of the research directions; with the development of the Internet of Things (IoT), smart home services have developed globally, enabling the capability to integrate and manage household devices (Alaa et al., 2017); Kang et al., 2017). Smart home services nowadays can set lighting, home temperature, music, or TV programs, depending on individual preferences (Markantonakis et al., 2016; Sanchez-Comas et al., 2020), or can be specifically targeted to support vulnerable social groups (Sapsi & Sapsi, 2019). Smart applications allow monitoring of home conditions when away from home, through temperature and humidity sensors, and allow users to distantly access home lighting or TV to imitate the human presence (Lévy-Bencheton et al., 2015; McIlvennie et al., 2020; Rajiv & Chandra, 2016). More advanced solutions offer living convenience, accumulating and analyzing living patterns of home residents (Sepasgozar et al., 2020).

R&D in the concept of smart cities works on the idea of creating an urban space with sustainable economic growth and quality life of its citizens (Caragliu et al., 2011). The main challenge of smart cities is to interconnect all possible services and people using them with the help of innovative technologies, such as 5G, sensors, robotics, IoT, and artificial intelligence (Patel & Doshi, 2019; Lim & Maglio, 2018).

Healthcare works on an extensive range of applications and devices, from remote monitoring of patients' conditions (Bruen et al., 2017; Taylor et al., 2021; Thomas et al., 2021), to coordinating and automating internal processes within smart hospitals (Kanase & Gaikwad, 2016; Moro Visconti & Martiniello, 2019).

In the transportation sector, the IoT helps in communication integration, control, and information processing across various transportation systems. Innovative solutions in the sector enable smart traffic control (Bean, 2002), support parking networks (Lin, 2015; Iacobescu et al., 2021), fleet management (Penna et al., 2017; Hussain et al., 2020), and transportation planning (Jan et al., 2019; Karami & Kashef, 2020), to name only a few.

The automotive sector could not be left behind, and has seen dynamic interactions between vehicle, infrastructure, and driver enable inter- and intra-vehicle communication. Smart systems development in the automotive sector started with systems like Collision Warning, Collision Avoidance, Intelligent Speed Adaptation, and other systems that rely on camera-based machine vision, radar, and high-accuracy digital maps and GPS (Bishop, 2000). Today more advanced sensing technologies and the combination of data from different sources, such as onboard video cameras, radars, lidars, vehicle sensors, digital maps navigated by global positioning systems, driver monitoring systems, and communication ability with other vehicles and software systems help to bring the intelligence of current automotive systems to a new level. Furthermore, computational intelligence, such as Fuzzy Logic, Neural Networks, Machine Learning, Knowledge Representation, and Probabilistic and Possibilistic Reasoning have become new building blocks for intelligent vehicle systems (Gusikhin et al., 2008). As a result, smart systems development blossoms in multiple directions, focusing on better *driver monitoring* (drowsiness detection (McDonald et al., 2018), driver distraction monitoring and prediction (Kanaan et al., 2019, Kircher et al., 2010), driving style recognition (Aljaafreh et al., 2012), driver workload estimation (Leeuwen et al., 2017)), better *context processing* (real-time 3D object detection (Yang et al., 2018), real-time traffic conflicts prediction (Formosa et al., 2020), recognition of driving context elements (Tchankue et al., 2013)), and development of *automated solutions*, such as automated parking and many ADAS functions with the range of advanced capabilities they provide.

2.4 USER

Today, there is a wide range of technologies available to support in-vehicle interaction. In many cases, the success of the technology is not limited by the technology capabilities themselves but rather by the capabilities of the human interacting with them (Harvey et al., 2011). Currently, the development focus has shifted from developing technology to considering how to integrate this technology with the driver (Walker et al., 2001) to simplify interactions for humans. A number of researchers point out the importance of implementing a driver-centered approach in order to identify and understand the needs of the driver within the context of driving (e.g., Heide & Henning, 2006; Stanton & Salmon, 2009). Walker et al. (2001) identified three main human-related factors associated with the use of information and communication technologies within vehicles: safety, efficiency, and enjoyment. Novakazi et al. (2021) add to this list drivers' comprehension of the system and its perceived usefulness. This study revealed that drivers' understanding of the system plays an important role in developing drivers' trust in the technology, especially for non-compulsory smart in-vehicle systems, while perceived usefulness is directly linked to the acceptance of the system by drivers. According to Harvey et al. (2011), the main aim for any in-vehicle system developer would be to:

1. Ensure driver safety by providing relevant information without distracting the driver from his primary driving task.
2. Enhance the efficiency of vehicle use by providing information about the vehicle, the vehicle system, and the driving environment.
3. Provide functions that are both pleasant and easy to understand in use.

Thus, the challenge for automotive OEMs would be to develop a Vehicle Information System that is capable of balancing all of these aspects.

2.4.1 User behavior

User behavior evaluation is key to discovering how users interact with the product and how well customer needs are addressed in a particular system design. In the frame of this research, the term user behavior is narrowed to driver behavior, meaning that only behavior related to the driving activity and the use of vehicle systems will be considered. Under driver behavior, we understand the set of actions a driver takes to reach a goal or complete a task while operating a vehicle. Driver behavior should also be viewed in consideration with the driving context and the specific actions expected in that context to achieve the desired outcome.

Understanding driver behavior is fundamental for building a successful product. The more developers know about the users, the better equipped they will be to make smart solutions that fit user needs. To understand and assess user behavior, one needs to refer first to two closely related concepts, namely Usability and User Experience, described in the following sections.

2.4.2 Usability

Usability is one of the main concepts when talking about driver behavior and driver interaction with the product. Interaction with a product that is easy to use and understand, increases users' productivity, decreases the learning process, and enhances the user satisfaction of the product itself. The main advantage for users is that they can perform their tasks easily and efficiently. Good usability of a particular product when comparing with similar products usually means the user would choose that product in the future. Good usability positively increases the reputation of the product and most likely would lead to an increase in sales. Therefore, the main goal for usability engineers is to construct a system or product that people find usable and will use (Ovaska, 1991).

Usability definition

Although the term usability is widely in use, there is no agreement on the exact definition (Abrahão et al., 2017). Different opinions regarding the way to measure usability, together with the different fields where usability is practiced, bring many similar definitions together (Folmer & Bosch, 2004). Nielsen (1993) describes usability as an aspect that influences product acceptance. He classified usability through five usability attributes: learnability, efficiency, memorability, errors, and satisfaction. Nielson's classification, together with the definition from ISO/IEC 9241-11 standards (1998) that defines usability as *"the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use"*, are two of the most widely accepted definitions in practice. Thus initially, usability was more focused on an outcome of interaction rather than on the quality of the product the user was interacting with. In the later standards (ISO/IEC 9241-210, 2010), usability is defined from two perspectives: as the quality of the product and as the outcome of interaction related to its quality in use (Abrahão et al., 2017).

According to the classification made by Bruno & Al-Qaimari (2004), usability consists of four common factors that have an impact on the whole interactive system: the user, the technology, the task, and the context of use. Consequently, the author adopted this definition in the research. The author assumes that only an understanding of the user's behavioral model and technical limitations of the interactive systems within the specific context of the system's use, including the analysis of the influence of external conditions, can lead to the successful development of an interactive system that meets users' requirements.

Furthermore, according to Peham et al. (2014), usability could be described by reference to the two following processes:

Learning process – the dynamic process that could be described as a process of gaining knowledge by studying, practicing and improving specific skills. Learning cannot be developed instantly but develops over time as experience increases. When the learning process comes to an end (when a user has reached stable user performance that doesn't change significantly over time), the usage process takes place.

Usage process – presumes that the driver has learned how to use the product, and the usage process measures how easy the product is to use once it has been learned. Figure 8 represents the improvement of user performance skills during the learning and usage processes.

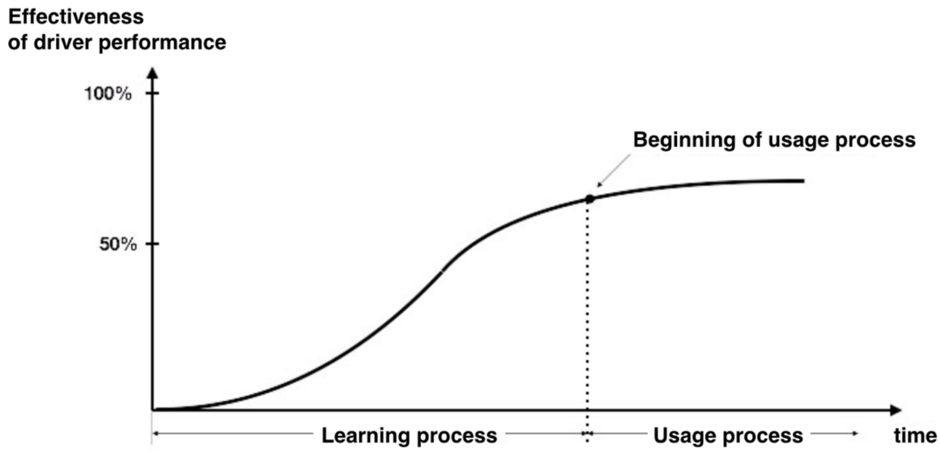

Figure 8. Learning and Usage processes in a User Performance development curve.

In this research, the author focused only on the usage process evaluation, since the learning process requires a different set-up for the study where the previous driver experience is considered, and data collection starts from the first interaction with the evaluating system.

Usability attributes

To be able to measure usability, a definition of usability attributes is required. Many attempts have been made to define the list of attributes for usability assessment. However, no agreement regarding a unified view on usability attributes has so far been reached. The digitalization trend for complex products, such as mobile phones, computers or cars, has consequently increased the convergence between the computer science, telecommunication, and engineering fields. This has only boosted the complexity level and introduced new types of interaction intended to help a user in communication with technology (e.g., touch screens, voice commands, gesture interfaces). Such a dramatic change in the interface frameworks forced usability engineering to engage a large number of specialists within various disciplines. As a result, the usability attributes list can vary in different fields and for different products.

2.4.2 User Experience

Another concept highly related to user understanding is the concept of User Experience (UX). According to ISO 9241-210, UX is defined as *"a person's perceptions and responses that result from the use or anticipated use of a product, system or service"*. UX is the umbrella-term that *"takes a broader view, looking at the individual's entire interaction with the thing, as well as the thoughts, feelings, and perceptions that result from that interaction"* (Albert & Tullis, 2013). Roto et al. (2011) have a similar view on UX, simply defining it as experience generated by interacting with the system. Forlizzi & Bettarbee (2004) describe UX as people's interaction with the product and the overall emotions resulting from this interaction. The Nielsen Norman Group (NN/g conference, 2008) illustrated the UX scope by encompassment of the utility, usability, and desirability of the product (see Figure 9).

Although this research is heavily focused on interaction with the system, at this stage, the author avoids using the UX term since vehicle data does not support an assessment of driver perception, which is the part of overall emotions resulting from the interaction.

Nevertheless, the author positions this research in the field of UX, but does not claim to have performed a data-driven assessment of UX. Primarily, it is the driver's interaction with the system in the long term that has been assessed, which allows us to reflect on specific UX metrics that focus on driver behavior or attitude towards the evaluated subject/object.

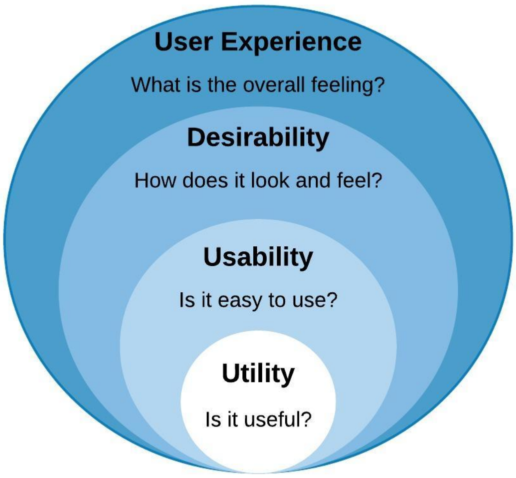

Figure 9. The scope of User Experience (adapted from NN/g Conference, 2008).

2.4.3 Methods for driver behavior assessment

According to Ivory & Hearst (2001), there are 132 documented usability evaluation methods (UEMs), which were derived mainly for web user interfaces assessment. These methods are divided into five classes: testing, inspiration, inquiry, analogical modeling, and simulation. However, if compared to the complex interfaces that include a physical interface in combination with a graphical interface placed in multi-mode screens, the number of applicable methods is very limited. In this research, the author is dealing with the already launched product, without the ability to change its design. Methods for this type of evaluation are usually narrowed to inquiry methods, such as surveys, interviews or user feedback.

Nielsen (1994) suggested using several evaluation methods that increase findings regarding different usability issues and cross-checking the evaluation results. Two Comparative User Testing studies, CUE-1 and CUE-2 (Molich et al., 1999), confirm Nielsen's suggestion by demonstrating the lack of consistency and systematic approach to usability evaluations. Those studies demonstrated that usability findings performed for the same project could vary dramatically, depending on the usability team's area of expertise and the methods that usability experts chose for the evaluation.

Moreover, in the engineering world, it is difficult to support the decisions on the results of subjective evaluation. Usability experts often feel undervalued in comparison with the other engineers able to support their decisions with objective evaluation. Having all these challenges in mind, usability experts are continually looking for ways to improve the usability assessment quality. In particular, they are most interested in bringing objective methods into the field. For that reason, the idea to utilize explicit knowledge at the data level is attractive to usability engineers. The objective data analysis can provide an understanding of users in a better way, by looking at the learnability or usage dynamics, evaluating individual or group behavior, detecting the usability issues, and measuring their severity.

Qualitative research approach

In studies related to user evaluation, a qualitative approach is traditionally applied. Qualitative research methods focus on the quality of things, trying to explain, describe and discover the root causes of user behavior (Creswell, 2014; Merriam & Tisdell, 2015). Denzin & Lincoln (2011) describe this research approach as an attempt to understand things in their natural environment, by interpreting the phenomena based on the meaning that a particular user or group of users bring to them. Qualitative methods usually focus on gathering subjective impressions regarding system usage, rather than targeting specific user tasks or identifying the variables that cause specific user behavior (Orlovska et al., 2019a).

Main advantages of qualitative research:

- Qualitative research is the most appropriate for situations when we need an explanation of why different things are happening, what their nature is, and how they can be described.
- Deep, widespread evaluation is possible. Participants are usually able to freely express their opinions, which helps to build a discussion and elaborate on what they mean.
- The human factors in the form of user perception are the primary interest of qualitative studies.
- Occurring events can be observed in their natural context without reducing the complexity of system, processes or tasks.
- Qualitative approaches have a well-established methodology, based on UEMs, summarized by Ivory and Hearst (2001). These methods allow receiving user-related input at different stages of product development.

Limitations of qualitative research:

- Due to the relatively low number of participants, qualitative methods have no statistical significance, which means that the findings from the qualitative study cannot be extrapolated to the larger population sets with the same confidence level (Ochieng, 2009).
- Frequencies of different issues detected through qualitative research are difficult to measure. As a result, rare phenomena can receive the same attention from the researcher as more frequent aspects (Ochieng, 2009). A low number of participants also reduces the possibility of classifying users or the issues they experience.
- A qualitative researcher cannot be seen as an independent individual (Rovai et al., 2013). Research techniques and environments (the lab or the questionnaire), as well as the researcher's own perception, can bias participants' views on the evaluated object and affect the interpretation of the results.
- Qualitative methods are often criticized for their low reliability. Different results may be achieved with various participants or at a different time.
- Qualitative studies are time-consuming. If stakeholders need to take an urgent decision, then probably the qualitative study that takes months to be administrated is not an option (Sallee & Flood, 2012).

Quantitative research approach

Quantitative research often focuses on measurements that test hypotheses, determine an outcome and generalize conclusions (Denzin & Lincoln, 2008). Quantitative studies may produce valid and reliable data due to the possibility to control the measurements with the help of specifically created technical solutions. Quantitative data could be obtained by quantifying subjective user input, drawing from extensive user surveys, or by using an automated method for data collection.

Main advantages of quantitative research:

- Larger samples, compared to qualitative research, often make the conclusions from quantitative studies generalizable (Rovai et al., 2013).
- Statistical methods are primarily used in quantitative data analysis. Those methods are precise and rigorous, which helps to establish a certain level of trust in quantitative methods among engineers (Rahman, 2020).
- Quantitative methods are also useful when a systematic, standardized measurement is needed.
- Quantitative research is independent of the researcher, and therefore, the evaluation process is less biased by the interviewer's viewpoint, his/her appearance or questions (Rahman, 2020).

Limitations of quantitative research:

- Due to the reduced data feasibility, it is often not possible to measure the full complexity of human experience or perceptions. Therefore, the user experience can be divided into measurable areas and studied as parts (Rovai et al., 2013).
- Quantitative research allows what things happened and how frequently they happened to be seen but cannot determine underlying explanations of why those things happened (Bouwer et al., 2015).
- The use of quantitative methods may give the wrong impression of homogeneity in a data-set. For example, the measured user experience of vehicle-owners might not be applicable to non-vehicle-owners. Therefore, some applications of quantitative methods may require clarification for homogeneity within the group.

2.4.4 Current trends of driver behavior assessment in the automotive industry

Even though both qualitative and quantitative research approaches are broadly applied in the automotive industry today, a substantial number of studies are still conducted in isolation. Different evaluation groups of designers/engineers with diverse backgrounds are usually conducting studies that are based solely on qualitative or quantitative data, resulting in low cross contribution from one study to another.

The validity of results for these kinds of studies is always questionable, and therefore the need to combine different approaches is clearly recognized. Nevertheless, the results of different approaches are mainly used for the comparison or validation of their findings but do not aim to improve the quality of the studies. This could be explained by the low compatibility of qualitative and quantitative data, which often leads to the practice of prioritizing one of the approaches over another. A qualitative approach is mainly applied in user-related studies, due to long-term traditions amongst automotive OEMs. Quantitative research methods, in turn, are broadly used for the evaluation of a vehicle's mechanical parts and software but are rarely applied in user-related studies.

However, the rapid development of objective data sensors and the variety of information generated by the automotive production platforms clearly indicates a need for a new methodology that considers both approaches: extended quantitative data possibilities utilization, and qualitative insights. Since both quantitative and qualitative approaches have their strengths and drawbacks concerning user studies, an intelligent fusion of both approaches, implemented effectively, can improve the quality of user studies and increase the validity of the results.

While the mixed-method approach is widely described in the literature, the author's understanding complies with Johnson & Onwuegbuzie (2004), who define this as a type of research where the research team combines qualitative and quantitative approaches to achieve in-depth understanding and validation of the results. Moreover, Greene (2007) states that effectively designed mixed-method research can "...offset inevitable method bias".

2.4.5 Naturalistic Driving Studies

The key approach adopted in this research can be characterized as a Naturalistic Driving (ND) study. An ND study usually refers to a study that is not constrained by a strict experimental design where the data are acquired for a relatively long-term period, in the natural driving context and under various driving conditions occurring in a natural way. Data in ND studies are collected mainly from vehicle sensors data, GPS, vehicle apps, and/or data from video cameras (Fridman et al., 2019). Vehicles are instrumented in the most unobtrusive way, allowing users to perform driving activities undisturbed. The sensors data are collected and processed with the help of wireless technologies. The data collection is systematic, within several months' time-span, and includes each driving activity. The advantage of this approach is that the driver is not limited in his/her movements, time and frequency of driving. The driver uses the vehicle in his/her own way, which is extremely important in creating a natural environment for the ADAS user behavior evaluation.

The EuroFOT (European Field Operational Test) was one of the first large-scale projects focused on investigating possibilities to enhance safety and reduce the environmental impact of vehicles instrumented with ADAS (Benmimoun et al., 2013). Another project, named 100-Car naturalistic driving study, was conducted on the US market with the aim to evaluate driver safety in crash and near-crash situations (Neale et al., 2005). The MIT Autonomous Vehicle Technology (MIT-AVT) study, which was launched in September 2015, seeks to understand how driver-vehicle interaction can be designed to be safe and enjoyable (Fridman et al., 2019).

The above described ND studies have inspired a number of programs and organizations, such as SCOUT (Safe and COnnected AUtomation in Road Transport, 2019), CARTRE (Coordination of Automated Road Transport Deployment for Europe, 2019), SAFER (THE SAFER organization, 2019), SHRP2 (Strategic Highway Research Program 2, 2019), ADAS&ME (Adaptive ADAS to support incapacitated drivers Mitigate Effectively risks through tailor-made HMI under automation, 2019), and others. These initiatives aim to support the research field by exploring and developing the potential of ND studies further. The majority of the projects are supported by governmental organizations and focuses on the driver and traffic safety issues, investigating the driver behavior in crash and near-crash situations (Sander, 2017; Hatfield et al., 2017; Engström et al., 2018). The context-aware evaluation of driver behavior in the preceding moment is a critical factor in these studies, enabling investigation and explanation in detail of the driving behavior before the incident happens. Liang et al. (2016) underlined the importance of driving context analysis for detecting abnormal driver behavior, aiming to quantify the risks associated with various driver behaviors. Zhai et al. (2018) emphasize the importance of context-aware driver behavior evaluation, showing that integrating driving context provides reliable results regarding the driver behavior evaluation on the road. According to Papazikou et al. (2017) and Tivesten & Dozza (2014), the driving context is one of the most important factors for user behavior evaluation. Both conclude that the context might affect driver behavior, both positively and negatively. Further, Ahlström et al. (2018) emphasize the effect of the road environment on the development of driver sleepiness. Ahmed & Ghasemzadeh (2018) designed an automated method for heavy rain detection. They measured the impact of heavy rain on driver behavior, discovering a correlation between the driver's age and the speed chosen under heavy rain conditions.

2.5 VEHICLE

Driving the vehicle presumes the use of multiple systems at a time. The driver interacts with the car through different controls and informs from various onboard systems integral to the car. The workload generated by the accumulation of tasks can have a negative impact on driver performance. According to Seppelt & Wickens (2003), two tasks that need to be performed simultaneously will be carried out with less effectiveness than two tasks that do not have a time overlap. Therefore, in multiple task situations, driver workload and resources spent by the driver between concurrent tasks need to be considered. Apart from the tasks that require driver intervention, the vehicle gives sensory indications to multiple parameters of driving activity, such as acceleration, deceleration, traffic information, navigation service, and many other services. This information load also needs to be considered while evaluating the driver's behavior.

3

RESEARCH APPROACH

The primary purpose of this research is to generate new knowledge that is valuable both to academia and to current engineering practices. This research focuses not only on providing insights for the people dealing with the investigated phenomena in practice, but also on designing methods for more effective application of newly generated knowledge.

This chapter describes the research approach applied to this thesis. It motivates the choice of a particular methodology and explains how it was adapted for the needs of this research. A specific focus is set to clarify the relations between studies, appended publications, and the investigated research questions.

3.1 DESIGN RESEARCH

Many definitions of design research exist, depending on the application background. Research design, referred to in the engineering context, is usually described as a set of purposeful activities that help develop a product from a need to its complete realization. According to Blessing and Chakrabarti (2009), *"design is a complex, multifaceted phenomenon, involving people, a developing product, a process involving a multitude of activities and procedures; a wide variety of knowledge, tools and methods; an organization; as well as micro-economic and macro-economic context."* Hubka and Eder (1987) defined design science as *"the problem of determining and categorizing all regular phenomena of the systems to be designed, and of the design process. Design science is also concerned with deriving from the applied knowledge of the natural sciences, appropriate information in a form suitable for the designer's use."*

Research design can be considered to pass through three evolutionary phases: Experimental, Intellectual and Empirical (Wallace and Blessing, 2000). During the Experimental phase, which existed until the late 1950s, the activities and experiences of senior designers were most valued. However, their observations in the design process were relevant to the specific domain they described, and functioned within one technical field and, therefore, could not apply in a broader context. During the Intellectual phase stage, the emphasis was placed on creating a design basis using a variety of methodologies and principles of a design process. The Empirical phase started in the 1980s, when the number of studies involving empirical data collection began to grow. The purpose was to understand how designers conducted the design process. The Empirical phase investigated what impact new methods and tools had on these processes (Blessing and Chakrabarti, 2009).

3.2 AVAILABLE THEORETICAL FRAMEWORKS

Different theories and frameworks were introduced within the design research field, providing a theoretical basis to research in the product development domain. In particular, the following research approaches were introduced: Theory of Technical Systems (Hubka and Eder, 1987), Domain Theory (Andreasen, 1991), TRIZ (Altshuller et al., 1999), Axiomatic design (Suh, 2001), CK-Theory (Hatchuel and Weil, 2003), Function-Behavior-Structure framework (Gero and Kannengiesser, 2004), Design Research Methodology (Blessing and Chakrabarti, 2009), Mathematical Theory of Design (Braha and Maimon, 2013), amongst others. Despite the fact that different frameworks were introduced in the field of engineering design, there was no strict recommendation for the use of one method over another. The above-described frameworks demonstrate a different level of applicability in the research projects, depending on the traditions of the university department and particular research group.

3.3 METHODOLOGY APPLIED IN THIS THESIS

The research presented in this thesis is based on the Design Research Methodology (DRM) framework proposed by Blessing and Chakrabarti (2009). DRM is intended to fulfill two purposes: first, to understand the investigated phenomena, and second to submit the tools, methods, or guidelines that can be introduced in practice. DRM has strong relevance to the field of mechanical engineering and product development. Moreover, DRM provides a context to position the research and encourages reflection on the research approach and the choice of research methods, allowing the researcher to find new ways to deal with the investigated phenomena. In this research, the author applied DRM, partially due to this research framework being an accepted research tradition of the university department and research group. Following research traditions helps to better understand research and its phases, evaluate the contribution of studies to overall research, and plan for following research activities.

The framework consists of four main stages: *Research clarification, Descriptive study 1, Prescriptive study 1, Descriptive study 2* (see Figure 10). At the *Research clarification* stage, the current understanding of the research field and purposes needs to be clarified. At this stage, the overall research aim is understood, the research questions are set, and the research plan that supports the work at subsequent stages is provided. Consequently, *Descriptive study 1* aims to develop an understanding of the research phenomena and its influencing factors. At the next stage, *Prescriptive study 1*, the knowledge of the research phenomena generated in the *Descriptive study 1* takes into account and aims to develop new methods or tools that support the improvement of the existing model. *Descriptive study 2* aims to evaluate the applicability and effectiveness of the proposed design modification, focusing on the impact evaluation. To assess the research contribution, the success criteria that directly reflect on the desired research goals need to be set. These criteria will be used to judge the research outcome against set goals.

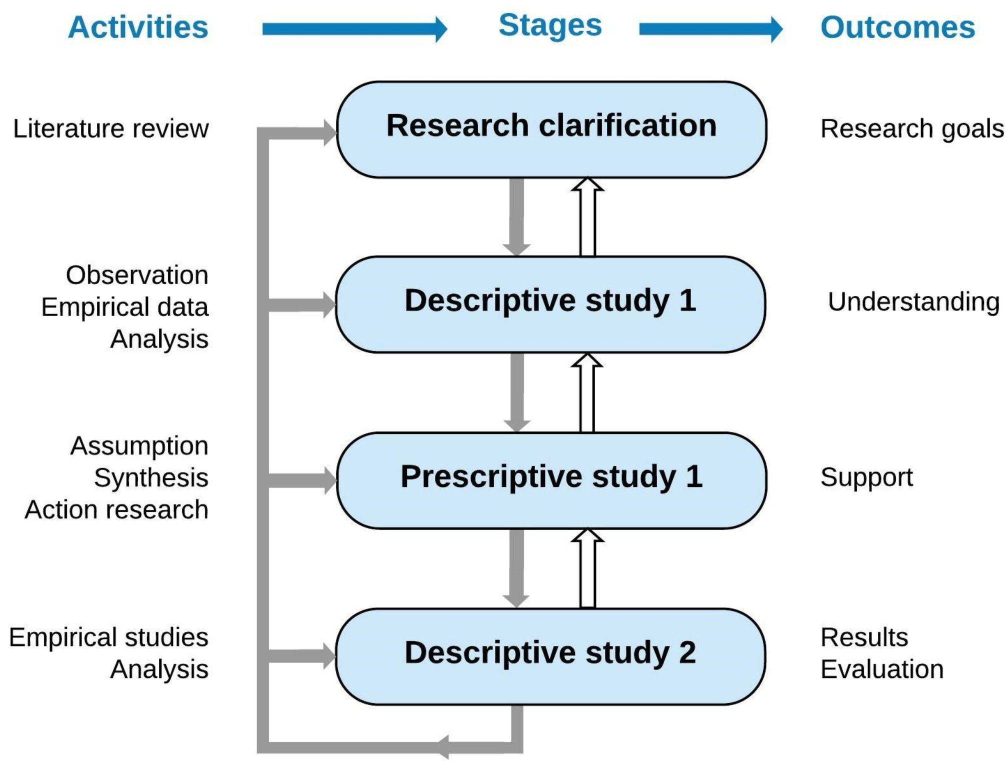

Figure 10: Overview of DRM framework stages.

One of the advantages of the DRM framework is that the implementation of the stages is not necessarily sequential or linear. Multiple iterations are possible between two stages and within every research stage, providing the flexibility to fit any specific research project. This flexibility allows the researchers to look for a variety of new ways for the phenomena investigation, and not directly follow the prescribed form. In this research, the DRM framework was also adopted due to its strong connection to the engineering field that provides a robust methodology that aims, through the understanding of investigated phenomena, to propose an improvement model that can be applied and verified in practice.

To verify that the goals of the research are achieved, it is necessary to identify the success criteria. Success criteria, according to Blessing and Chakrabarti (2009), relate *"to the ultimate goal to which the research project intends to contribute and usually reveal the purpose of the research"*. This research aims to design a reliable method for the data-driven evaluation of driver behavior and integrate a vehicle-data-based assessment into existing practices to enhance the quality of the obtained results. The ultimate goal of this research is to propose and implement a new design that utilizes these behavioral data in real-time to provide drivers with the support that enhances driver experience with vehicle systems.

The following sections describe how the research methodology was applied in the course of this thesis. The author will explain which research questions were investigated in the appended papers, what research methods were used, what type of results were achieved, and how this work was distributed among DRM's main stages.

3.3.1 Research questions and DRM phases

This research aims to investigate and design methods for effective vehicle data utilization in driver behavior assessment and to generate new approaches that help create a value based on these data to support drivers' individual needs. To achieve this goal, a number of research questions were specified.

RQ 1 *(What vehicle data are relevant to support the understanding of driver behavior?)* focuses on investigating interrelated factors for the driver-behavior assessment process, deriving data points needed for understanding driver-system interactions within the specified use context, and exploring the limitations that prevent the organization of more effective data collection. **Paper A** focuses on identifying the needs of UX experts related to the implicit data and analyzing the constraints that prevent the collection and use of these data. Despite the potential of implicit user interaction data for improving the UX of a product, previous work shows that these potentials are not (yet) leveraged for automotive IVISs. Therefore the additional focus of **Paper A** is given to investigating how to leverage the potential of implicit vehicle data to enhance UX activities and user-related studies. As a next step, in **Papers C & D**, the author designed the dataset and collected the data to illustrate the ability of vehicle data to contribute to driver behavior understanding. **Papers C & D** together provide comprehensive results on driver behavior evaluation based on an historical dataset. Finally, in **Paper F**, the author proposes the framework for real-time data utilization in driving coach systems and describes data points contributing to driver behavior assessment in the driving coaching framework. Based on this framework, a more comprehensive dataset was compiled and a full-scale evaluation of driver behavior was performed. Additional work focused on describing current limitations that restrict adding more user-related data into the measurement.

RQ 2 *(How can the data-driven approach be incorporated into existing methods for driver behavior evaluation?)* is about how to position the objective data-driven analysis in the evaluation process so that it is accepted in practice. **Paper A** explores the applicability of objective data analysis in the overall process of UX design and evaluation in the automotive context, while **Paper B** provides the design of the mixed-method approach, for the complete incorporation of the quantitative approach into the qualitative assessment of in-vehicle systems. Further, **Papers C, D & F** apply the methodology designed in **Paper B**, verifying it in practice.

RQ 3 *(How can vehicle data be used to support users' adaptation to smart in-vehicle systems?)* refers to possible applications of knowledge generated, regarding driver behavior based on vehicle data to improve driver behavior and enhance drivers' interactions with the system. **Paper E** proposes the approach of data-driven driver coaching to improve driver behavior with the vehicle system. Driving coaching monitors driver behavior in the interaction context with the system and provides real-time suggestions for enhancing or optimizing this behavior. **Paper F** generalizes the work presented in **Paper E** into the driving coaching framework that describes what data need to be collected to make this coaching feasible. Based on this framework, **Paper F** also introduces a fully developed Driver Coach application that has been tested under real driving conditions. The results of **Paper F** focus on evaluating the effect of this coaching on driver behavior.

According to Blessing and Chakrabarti (2009), a DRM framework should not be interpreted as a strict and linear research process. The allocation of the research questions in the DRM framework has particular reasoning. The exploratory studies performed in this research focused on defining the relevant dataset for user-behavior evaluation and investigating potential ways for these data applications in system design. The results revealed technical and conceptual limitations, restricting full-scaled vehicle data collection and utilization. Thus, the descriptive study was focused on overcoming the limitations of data collection and improving the methodology for evaluating driver behavior with in-vehicle systems. In parallel, the author investigated how behavioral data can be used in practical applications to help users improve their experience with systems. In the prescriptive study, the author promotes a mixed-method approach for driver behavior evaluation, where qualitative and quantitative methods contribute to insights of each other, allowing a complete understanding of how in-vehicle systems are used. Additionally, in the course of the prescriptive study, the author proposed the real-time personalized driver coaching approach where vehicle data are used to improve driver behavior. The distribution of the appended papers in the context of DRM phases is depicted in Figure 11.

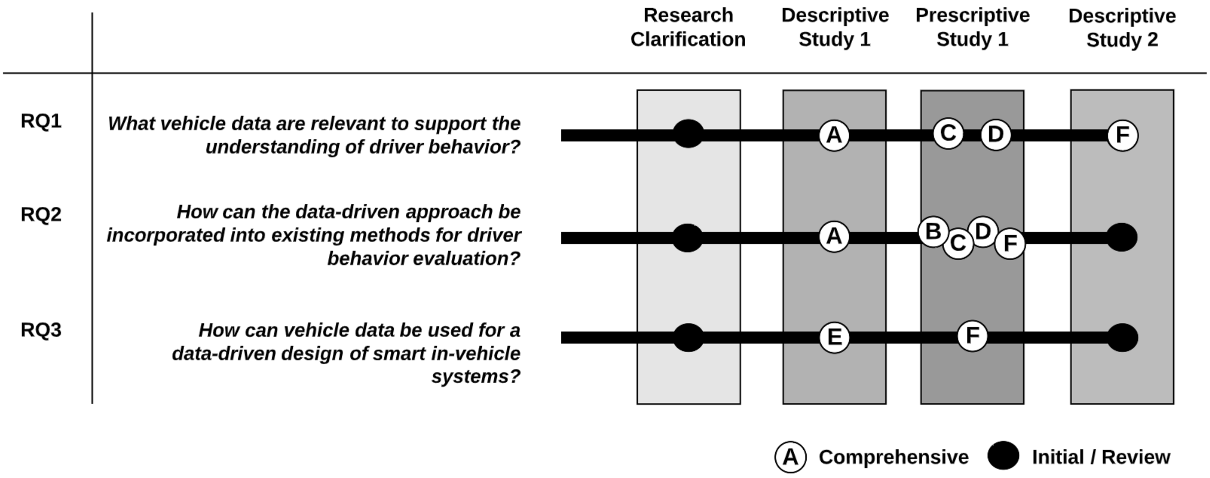

Figure 11: Distribution of papers A-F in the context of the DRM framework.

3.3.2 Types of results

Several types of results were achieved in the presented research. Descriptive study results provide empirical and statistical data that lead to a better insight on how vehicle data analysis contributes to user behavior understanding. **Paper A** collected empirical data to understand the limitations and potentials of vehicle data for UX activities across different automotive OEMs. **Paper B** proposed the design of the mixed-method approach for comprehensive ADAS evaluation. Subsequently, **Papers C & D** collected empirical and statistical data to prove vehicle data's ability to contribute to driver behavior understanding, confirm the applicability of the mixed-method approach, and provide reliable results regarding complex ADAS evaluation. Further, **Paper E** proposed a theoretical approach for a real-time personalized driver support system. Subsequently, based on the results of **Paper E**, **Paper F** presented a general framework for driver coaching and designed the case study to verify the proposed framework. Additionally, **Paper F** collected empirical and statistical data to demonstrate the ability of this data to contribute to a better understanding of driver behavior.

3.3.3 Methods used

There are numerous approaches for collecting data within design research, such as samplings, interviews, group interviews, surveys and observations, and others. The methods used in the course of this research are presented in this section.

A systematic **literature study** was performed in this research. The main goal was to understand the knowledge foundation, to be able to map the proposed methods and definitions, as well as to identify any existing gaps in the knowledge related to data-driver user behavior evaluation. Moreover, an extensive study of the OEM's internal documentation studies was performed. Among others, the documents consisted mainly of adopted attribute structure and its detailed descriptions, lists of functional and technical requirements, and methods for evaluating these requirements, technical reports, and plans of operations. The author participated in weekly internal follow-up meetings, observing the practical approaches to the investigated phenomena.

Interview studies are typically classified as structured, semi-structured and unstructured. According to Yin (2013), the interview is a widely used method in qualitative research, aiming to collect respondents' subjective opinions on the investigated issues. In this research, only semi-structured interviews were performed. Semi-structured interviews include elements from both structured and unstructured interviews and "a fixed set of sequential questions is used as an interview guide, but additional questions can be introduced to facilitate further exploration of issues brought up by the interviewee, thus almost taking a form of a managed conversation" (Cachia and Millward, 2011). Consequently, all interviews were transcribed verbatim, then coded and analyzed with the help of qualitative data analysis software, NVivo 12 (NVivo, 2019). Two independent coders examined the first transcript to identify different themes or nodes. In the next step, the themes were reviewed and discussed in order to determine coherence and minimize subjective discrepancy. After that, the interviews were coded by each researcher separately, and a final session was held, where the open questions and themes were discussed to review the quality of the coding.

A **field study** is a universal method for collecting data about users, user needs, and product requirements that involves direct or indirect observation and interviews. Normally the data collected are about task flows, user performance, detected issues and any types of inefficiencies in the user environment (Rosenbaum, 2002). Studying driving behavior in the dynamic context is a fundamental characteristic of Field Operational Tests (FOT) and ND studies. The ND study usually refers to the study not constrained by a strict experimental design, where the data are acquired for a relatively long-term period, in the natural driving context, and under various driving conditions happening in a natural way.

A ND study was designed and performed in the course of this research. Vehicles were instrumented in the most unobtrusive way, allowing drivers to perform driving activities undisturbed. The vehicle sensors' data were collected and processed with the help of wireless technologies. The data collection was systematic, within the time span of seven months and included each single drive cycle. The ND data included a combination of CAN bus data, GPS data, cloud data, external data provided through additional applications (e.g., the navigation data) that affect driver behavior or system performance. The data analysis was conducted with Power BI software for statistical analysis (Power BI Microsoft, 2021). The data was analyzed in four different layers of abstraction: single drive cycle (DC) evaluation layer (if something indicated unusual or interesting user behavior that needed in-depth investigation), one-driver evaluation layer (focused on in-depth user behavior evaluation of the same driver), groups comparison layer (based on the comparison of user behavior between different user groups), and overall assessment layer (based on the average calculation for all users). A detailed description of these abstraction levels can be found in the Methods chapter of Paper D. In general, the ND data analysis was based on the use of statistical methods that provide statistical significance and reliability to the obtained results. A more detailed description of how the above-described methods were integrated into the research design in the appended papers is described in Chapter 4.

3.3.4 Validating the results in applied research

To establish the quality of the research, validation and verification of the results and methods are required. In the context of engineering design, verification refers to internal and external completeness and consistency, whereas validation refers to the justification of knowledge claims (Barlas & Carpenter, 1990). Nanda et al. (2000), stated the need for an interdisciplinary approach to address complex problems in the research.

Thus, to achieve the validity of the results in this research, a cross-validation approach was used. *Cross-validation* refers to the procedure by which sets of scientific data generated using two or more methods are critically assessed. Cross-validation can have two dimensions:

analytical data validation and method validation. Analytical data validation in this research is supported by the sequential mixed-method approach (used in **Papers C, D** and **F**), which helps to cross-validate the findings, comparing the results of qualitative and quantitative evaluation.

The method validation can be performed through *Validation by acceptance* that focuses on having new scientific contributions accepted by scientific and industrial experts within the field. Adoption of the method in the industry and publishing the method in scientific journals are the first indicators of validation by acceptance.

Verification of the results can be ensured by *Logical verification*, which provides the analysis of coherency, completeness of results, and consistency of internal/external elements. Validation and verification of the results from this research will be further discussed in section 5.2.

4

RESULTS

This chapter presents the core findings from the papers appended to this thesis. The main focus, however, is given to the achieved results. For more detailed information, please refer to the full texts of the papers at the back of this thesis.

4.1 PAPER A

4.1.1 Purpose

In general, the study aims to explore and explain the specifics of the automotive field concerning data-driven approaches in UX design activities. This paper is designed to help automotive OEMs supply their UX experts with sufficient methods to integrate User Data into their daily work. The authors give recommendations on what UX specificity need to be considered when building an automotive data logging and analysis framework. To this end, the authors elaborate on the technical infrastructure and identified limitations, the current way of working, and how current, primarily qualitative, methods can be triangulated with data-driven methods. By combining the knowledge regarding the limitations that apply to the automotive domain, the UX experts' needs, the methods they use, and the triangulation potentials, this paper aims to bring data-driven methods and UX activities closer together to unleash untapped potential.

4.1.2 Method

A Multiphase Mixed Methods approach is adopted and modified to fit the research objective of this work. The overall design incorporates four studies, two of which are interview studies with industry professionals, and two are case studies focused on investigating vehicle data availability for user-related research. Along with the results of the interviews, which directly contribute to the study's overall goal, we also applied the methodology of Action Research to observe and critically analyze the ongoing development in two field studies, to combine academic knowledge and actual practical challenges. The Action Research methodology aims to gain theoretical knowledge based on researchers' deep and direct understanding when interacting with the client organization. Thus, the action research method builds a co-production model between researchers and practitioners, which is fitting for assessing the issues raised in this paper. Presented below is an overview of how individual studies are designed and their contributions to the overall work.

Paper A consist of two parts and four studies. Part A includes Study 1 and Study 2, which were carried out in collaboration with a leading Swedish OEM and combined using an Explanatory Sequential Mixed Methods design. The design of Explanatory Sequential Mixed Methods consists of two distinct phases, in which the action research method (Study 1) was preceded by a qualitative interview (Study 2). In Study 1, the implementation of a design for collecting and analyzing quantitative data in a natural driving study revealed several limitations regarding company data-related processes. Subsequently, these limitations were explored in more detail in a qualitative interview with company professionals (Study 2) to understand the constraints for OEMs of the use of data-driven methods. The triangulation of the two studies helped better understand the underlying causes of practical limitations.

In contrast, part B, consisting of Study 3 and Study 4, was conducted using an exploratory sequential mixed methods design. Under this design approach, the interview (Study 3) first explores professionals' needs, concerns, and challenges to use these insights to implement data-driven user behavior assessment methods further. A sequential quantitative case study (Study 4) aims to integrate data-driven methods and tools into an OEM's UX design process, using the potential identified in the previous interview.

Despite the parallel design of the Explanatory Sequential Mixed Methods approach (part A) and Exploratory Sequential Mixed Methods approach (part B), all four studies are used to complement, enhance, and validate the results of each other. A series of workshops was organized to integrate the results of individual studies. During the first workshop, the authors created a mapping between different themes to determine which points were validated or enhanced by another study. In the second workshop, the authors discussed and identified the most critical issues for the UX design process. As a result of this work, a common understanding of current data-driven methods in the automotive UX area has been developed.

4.1.3 Main results

In this study, the authors explore the UX role in the product development processes to understand how UX design activities are distributed throughout the UX design phases in the complete product development life cycle in the automotive sector. This understanding provides better insight of the potential, and addresses limitations of implicit quantitative data that can be collected automatically in real-time.

As part of the results, the authors first derived a list of limitations and discussed its consequences for applying data-driven methods in the UX design and evaluation processes. As seen from the limitations list (see Figure 12), automotive product development specificity explains most of the collected issues. Current practices in the automotive sector, regulations that have to be met, priorities set, methods used, and the vision on digital product development and UX affects how the vehicle is looked at today. Vehicle performance development is still prioritized over user-centered development. UX design plays an important but secondary role. Therefore, the developed solutions for data management are more focused on satisfying performance verification requirements than the data requirements introduced from the UX development side.

Subsequently, the derived limitations were linked to the need for implicit data that UX experts clearly expressed during interviews and field studies (see Figure 12). While some needs are directly related to constraints, some describe explicit requirements that are not related to current technical shortcomings, namely insufficient transparency, specification, and documentation of implicit vehicle data, lengthy processes, and a lack of integration of data-specific requirements in the early stages of product development.

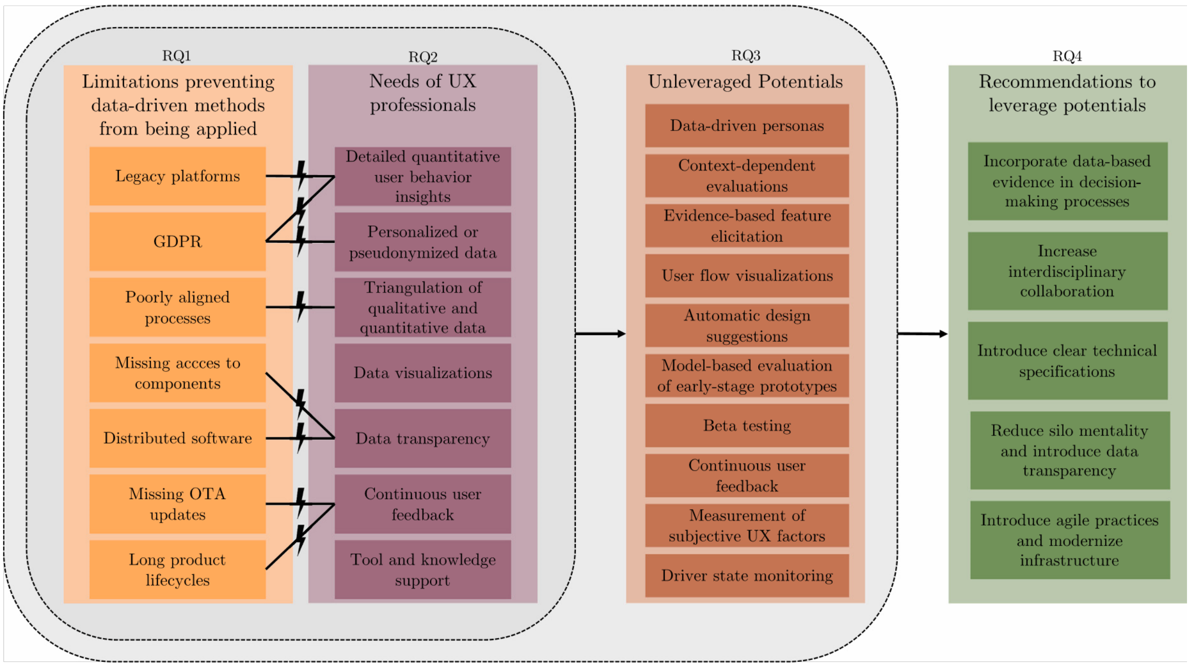

Figure 12. Summary of results for Paper A. The solid lines and lightning bolts indicate which specific limitation conflicts with which need. The dotted outlines and arrows indicate the consideration of combined previous results.

Our results show that approaches based on vehicle data can improve the UX design process in many respects. To make the current design process more data-driven and thus more user-oriented, UX experts need detailed user interaction data, tools, and visualizations that make complex analysis results easily accessible.

However, our results show that several conflicts need to be resolved to use the extracted potentials and meet the needs of UX experts. The authors, therefore, recommend that automotive OEMs re-think their current decision-making process when it comes to feature and requirements elicitation, and involve data-based evidence when making design decisions that affect user-facing features. The authors additionally argue that the technical requirements for logging detailed user interaction data must be integrated into early product development processes. The interdisciplinary collaboration between data scientists and UX experts needs to be strengthened, relevant technical and legal information needs to be transparently distributed within the OEMs, and the ever-existing problem of silo mentality needs to be approached.

4.2 PAPER B

4.2.1 Purpose

In this research, the author continuously stresses that both qualitative and quantitative approaches can effectively support the user behavior evaluation process. Different types of user data applied in these approaches contribute to different kinds of knowledge regarding the understanding of user behavior. Traditionally, qualitative methods are more often used for user behavior evaluation. However, recent advances in data technology increase in-vehicle connectivity and open new capabilities for obtaining new objective usability data. Therefore, the combination of qualitative and quantitative methods can lead to a better research approach than using each of them in isolation. Thus, in this study, the authors propose a new, improved methodology design for user behavior evaluation. We take ADAS as an example of the vehicle systems for the assessment, and design the method based on intelligent quantitative and qualitative approaches consolidation, aiming at a substantial improvement of methodology design for driver behavior evaluation and improved validity of the results.

4.2.2 Method

In this paper, an imperative study was performed. Based on previous findings (Orlovska et al., 2018a and Orlovska et al., 2018b), where the author investigated vehicle data abilities and limitations to support the user-related studies, the holistic approach for in-vehicle systems usage evaluation was formed. Analysis of data feasibility and current practices at the OEM helped reflect on the effectiveness of the methods and led to the proposal of the explanatory sequential design for in-vehicle systems usage evaluation. Thus, the explanatory sequential mixed-method design became a logical continuation of previous work reacting to improved data availability and increased need for objective data to support decision making.

4.2.3 Main results

The proposed explanatory sequential mixed-method design for vehicle support systems includes four major phases: (i) initial set-up of the study; (ii) quantitative evaluation; (iii) qualitative evaluation; (iv) feedback loop (see Figure 13).

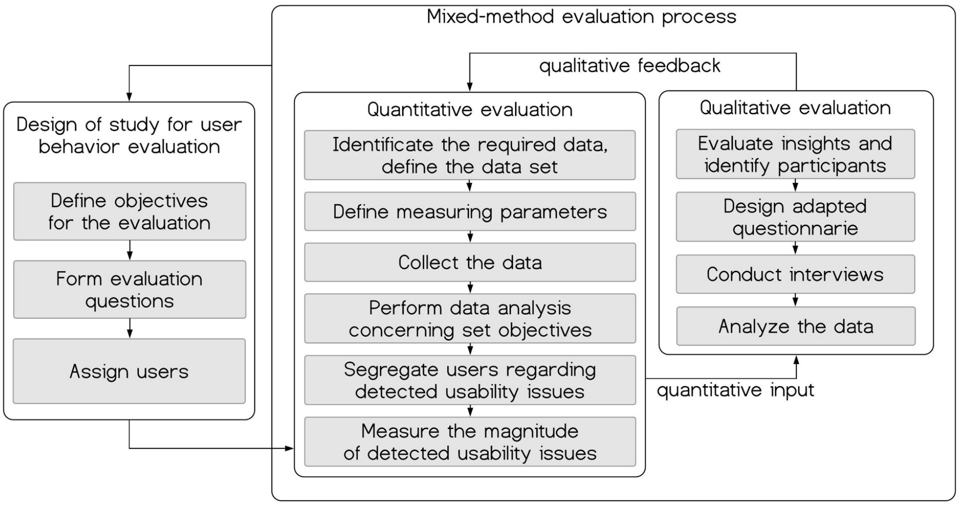

Figure 13. Design for mixed-method user behavior evaluation of ADAS.

According to the proposed design, the study design for user behavior evaluation requires an initial set-up. First, the study's main objectives and focus need to be set. This helps to design evaluation questions. The study can focus on identifying any trends in user or system behavior or looking for correlations in user behavior to reveal possible usability problems. Second, when the focus of the study is set, relevant drivers for the evaluation need to be assigned. Drivers' background, previous experience regarding the evaluated system, gender, age, work responsibilities, and other parameters can bias the results if drivers are not chosen correctly.

During the quantitative evaluation phase, vehicle data collection and analysis are performed. This assessment requires the development of a dataset where each assessment question is associated with a set of data points that support the answer to a specific question. In addition, the measured parameters, such as the length of the study, the number of participants, the number of context parameters, etc. need to be defined. Data collection designed as part of the ND study was proposed as the most natural way of unobtrusive driver-system evaluation in a real environment. During the ND study, performance data for both the driver and system needs to be collected, together with contextual information that affects both driver and system behavior.

The subsequent application of the qualitative study is built on the results of the quantitative study, aiming to explain the identified phenomena. Semi-structured in-depth interviews with drivers from the quantitative phase were chosen as an appropriate method, aiming to explain and uncover detected issues. The qualitative study design, therefore, focused on the clarification of the subjective reasoning of the drivers inside the detected target groups to understand the specific user behavior.

In a final step, the authors propose to feedback the qualitative findings to the quantitative level for further verification. To achieve a complete understanding, it is helpful to examine if a particular user explanation, received during the qualitative study, applies every time in the same context, and how other drivers behave under the same conditions. This type of analysis helps to understand if the qualitative explanations can be generalized. The mixed-method feedback loop can also help to identify other relevant data that can be useful in the next round of the quantitative assessment. For example, if a specific interrelation between user and system was detected during the qualitative data analysis, the evaluating team can examine the possibility to include additional data points into the quantitative evaluation for better support of the identified phenomena. Thus, this approach contributes to the further development of a quantitative dataset.

Additionally, this paper presents preliminary results of an entirely quantitative ADAS assessment, confirming the feasibility of the proposed method design. The data analysis was carried out, focusing on the defined objectives and questions formulated beforehand. The contribution of quantitative evaluation for the ADAS functions (namely ACC and PA) usage was measured. The qualitative study helped to: (i) measure the usage level for ADAS functions; (ii) differentiate patterns/trends in user behavior by clustering drivers who behave similarly under the same conditions; (iii) evaluate and consider the system performance in the user study; (iv) understand that system availability varies for different users and depends on the conditions at the moment the activation request is sent; (v) detect specific usability issues and measure their magnitude; (vi) set several hypotheses regarding driver behavior based solely on the vehicle data analysis.

Thus, the inclusion of quantitative evaluation into an existing methodology contributes to a more efficient assessment of driver-system interaction in a defined context and more effective product development in a long perspective. Moreover, the authors believe that this sequential use of quantitative and qualitative approaches, and the feedback of the results into the evaluation process, can support designers and engineers within research and development to create synergies in the development process.

The conference paper outlining these results had the title *"Mixed-methods design for user behavior evaluation of automated driver assistance systems: an automotive industry case"* and was presented as a podium presentation at *ICED conference 2019 in Delft, Netherland*s, published in *Proceedings of the Design Society: International Conference on Engineering Design*.

4.3 PAPER C

4.3.1 Purpose

A full-scale study for ADAS evaluation was conducted with respect to the driving context as one of the major factors influencing driver behavior. The effect of stand-alone contextual variables of ADAS on driver behavior has been assessed by other researchers. However, a complete investigation of this topic is lacking. Therefore, this paper aims to investigate and understand how the driving context affects the use of ADAS. An additional goal of this paper was to apply in practice, and validate, the mixed-method design proposed in Paper B.

4.3.2 Method

The explanatory sequential mixed-method approach proposed in Paper B was adopted and modified for the current research needs. The sequential use of quantitative and qualitative methods (see Figure 14) aims to facilitate an integrated interpretation concerning the effect of the driving context on ADAS usage.

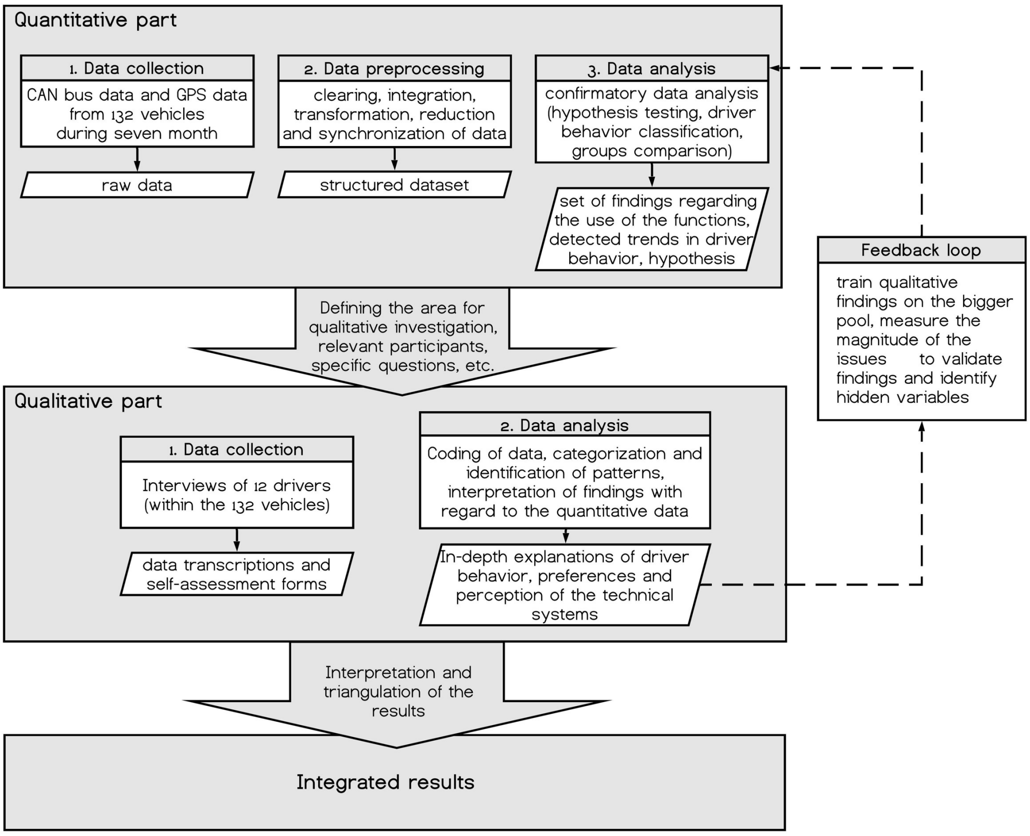

Figure 14. Explanatory sequential mixed-method design.

The particular approach proposes two distinct phases: a quantitative and qualitative evaluation. In the course of the quantitative study, ND data for both the driver and system performance were collected over a period of seven months. Data points that support the driving context understanding for ADAS were also included in the assessment. In total, data from 132 vehicles were collected. Consequently, in the data pre-processing step, different techniques were used to clear up, integrate and transform the raw data into the structured dataset. All corrupt and inaccurate records were removed from the dataset. The data were synchronized in time, providing order and structure for the initial dataset. Finally, statistical data analysis of collected data was made with the help of software for statistical analysis (Power BI Microsoft, 2019). The data were analyzed in four different layers of abstraction: (1) single driving activity evaluation (if anything indicated unusual or interesting user behavior in one driving activity that needed in-depth investigation); (2) one-driver evaluation (focused on in-depth user behavior evaluation of one driver); (3) groups comparison (based on the comparison of user behavior between different user groups); and (4) overall assessment (based on the average calculation for the complete pool).

Subsequently, the qualitative phase was performed. The qualitative phase was designed based on quantitative study results with the main purpose to explain emerging phenomena. In the course of the qualitative study, semi-structured interviews were held with 12 respondents participating in the quantitative study. The aim of the interviews was to explain and uncover the human perception of the driving context and its effect on system usage. The interview data were subsequently transcribed and analyzed by two independent coders using NVivo Software.

The purpose of the triangulation design was to revise the completeness of the quantitative dataset by identifying relevant data points from the qualitative study and verifying their importance based on the complete vehicle pool. Thus, the feedback loop from the qualitative findings was utilized for further investigations at the quantitative level. The qualitative insights were tested on a wide range of users, aiming to cross-validate the hypothesis based on quantitative evaluation and qualitative explanations.

4.3.3 Main results

This study revealed the effect of the driving context on ADAS performance and driver behavior. Therefore, the authors advocate the ADAS evaluation approach where the driving context will be considered one of the significant factors for evaluating support systems since the threefold interrelation between the driver behavior, ADAS performance, and the driving context is considerably high.

The quantitative data analysis in this study enabled the assessment of driver and system performance, as well as the driving context, including the weather, road, and traffic conditions. Based on quantitative data analysis, the authors measured the average ADAS usage for the complete vehicle fleet and the individual grade of ADAS usage. This knowledge helped the authors with driver categorization based on different use levels of ADAS functions. Further analysis revealed that the driving context, especially the road and traffic conditions, can significantly affect the scenarios that the two groups chose for ADAS usage. Therefore, the authors compared the groups' behavior and investigated the differences in how the groups handled the different driving conditions.

The consequent qualitative study verified the quantitatively detected differences in drivers' behaviors and contributed to the holistic interpretation of the results. The interview data analysis revealed that the driving context had a dual effect on driver behavior: (i) a direct effect because the driver has to consider the driving situation every time that he/she wants to activate the ADAS function; (ii) an indirect effect through system performance, that also depends on the driving context. The system may deactivate support due to existing system limitations. If the driver does not understand the deactivation causality reasons, he will perceive the system as not reliable. Thus, the context-dependency of system performance may impact driver perception negatively and decrease ADAS use for the group of drivers with a low understanding of the system's limitations.

4.4 PAPER D

4.4.1 Purpose

This paper is a direct continuation of Paper C. Both papers C & D are present results of the same ND study; however, they focus on different research objectives. In the previous paper on the same study (Paper C), the authors concluded that driving context affects ADAS use through system performance, showing that ADAS design limitations affect drivers' trust and willingness to use systems in the long term. Subsequently, in this paper, the authors further explore the underlying factors that impact users' understanding of the system and investigate how users interpret the system and its limitations, and what use strategies they can develop based on their understanding.

4.4.2 Method

The same explanatory sequential mixed-method approach as in paper C was adopted to achieve this study's objectives. Both quantitative and qualitative approaches were implemented to assess the effect of the drivers' perceptions on ADAS usage. The first phase consisted of quantitative data collection by conducting the ND study and classifying and analyzing the collected data to evaluate the use of the systems in combination with various contextual information, i.e., traffic and weather conditions and road types. The second phase aimed to clarify the data-driven findings through in-depth interviews with the participants from the ND study. This phase focused on identifying and explaining the impact of driver understanding on ADAS use. The qualitative study design was based on the trends detected during the quantitative study phase and intended to explain and clarify the emerging phenomena and usage behaviors through the explanations from targeted study participants. Figure 15 illustrates the sequential mixed-methods design through the different phases and how the results conflate into a holistic understanding of driving behavior with ADAS.

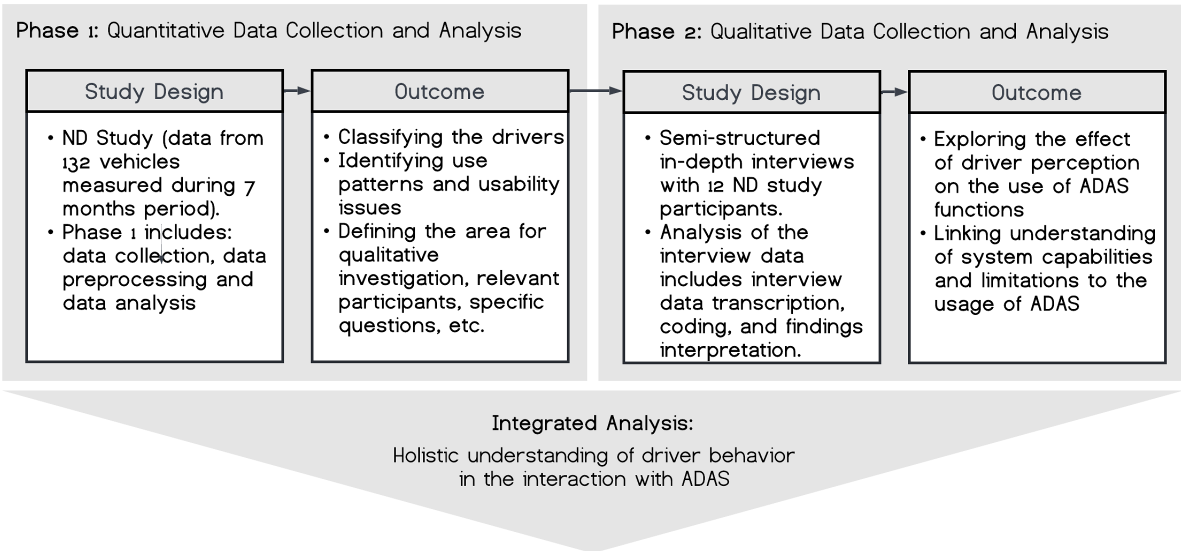

Figure 15. Explanatory sequential mixed-method design.

In the quantitative phase of this study, the driver and system performance in various driving conditions were logged, providing precise measurements and helping identify different use patterns and trends during the use of the ADAS. In total, ND data from 132 vehicles was collected for seven months. Consequently, in the data pre-processing step, the data were cleared up, which helped remove all corrupt and inaccurate records from the dataset and provide order and structure for the initial dataset. Finally, statistical data analysis of collected data was made with the help of software for statistical analysis (Power BI Microsoft, 2019).

Subsequently, in-depth interviews were performed to elicit explanations and reflections on the detected driver behavior during the analysis of the ND study, aiming to identify human-related factors influencing the system usage. Semi-structured interviews were held with 12 respondents, a subset of drivers participating in the quantitative study. Thereafter, the interview data was transcribed and analyzed by two independent coders using NVivo software.

The integrated analysis was conducted with regard to the findings identified during the quantitative phase to discover correlations with the predetermined results and patterns observed from the quantitative data evaluation. After the thematic analysis of the interviews, the quantitative analysis results and identified relevant aspects influencing the drivers' usage of the two systems, ACC and PA, were revisited to find explanations for the trends observed in the data. This approach helped investigate whether the qualitative data supported the identified trends from the qualitative study.

4.4.3 Main results

This study resulted in several findings that reveal the effect of drivers' understanding on their behavior.

First, drivers tend to develop static use strategies regarding the functions. The data show that most drivers stick to their chosen behavior and follow the established use strategy without revising their behavior in response to the situation on the road. The change in the context doesn't make drivers reflect on it and reassess their use strategy, meaning that drivers need additional stimuli that shift their attention to reassess the effectiveness of their behavior.

Second, even though drivers established diverse use strategies, all of them agreed on the perceived usefulness of ADAS functions, pointing out such positive aspects as added comfort and safety and reduction of mental and physical workload. These factors are clearly perceived as positive values that encourage the usage of ADAS functions.

Third, since ADAS functions provide poor feedback to the driver, the driver should have the independent ability to understand the ACC and PA performance. The more that drivers are aware of ADAS capabilities and limitations, the easier it would be for them to understand the system behavior. The understanding that meets drivers' expectations contributes to a more positive perception of ADAS performance. Thus, realistic expectations of the systems develop better trust in ADAS systems, which positively affects the usage of these systems. On the contrary, a poor understanding of ADAS functionalities and limitations can create a negative experience with ADAS, creating the perception that drivers cannot rely on the performance of these functions. This can result in drivers refraining from using the system altogether.

These findings support the conclusion that ADAS use is influenced by understanding the system's capabilities and limitations, which is critical to building the necessary trust required when interacting with it. However, trust is calibrated throughout the use process. It can be affected by positive or negative experiences, making users adjust their expectations of the system and hence their usage strategies.

The results demonstrate that it is essential to design a guided learning experience to avoid profoundly negative experiences, support users in overcoming the threshold of using ADAS, and help them use these systems in the intended ways. In summary, better support for users in understanding system capabilities and limitations will forge acceptance of ADAS. Accordingly, this needs to be investigated to identify design strategies to enhance the learning experience.

4.5 PAPER E

4.5.1 Purpose

This article proposes a high-level design of real-time personalized support for PA users. A data-driven approach is a key idea of this design. It provides a context-aware evaluation of the dynamically changed traffic situation in real-time and focuses on promoting PA usage in varied traffic situations. The research presented in this paper aims to conceptualize the real-time personalized driver support idea and understand all interrelated forces that need to be considered in this type of support. The main goal of real-time personalized support is to explain to drivers what capabilities and limitations PA has and how it can be used more effectively in different traffic conditions by helping to identify suitable traffic conditions for PA activation. As an outcome of this support, we expect drivers to increase their understanding of the PA function, develop confidence in PA context identification, and eventually increase PA use.

4.5.2 Method

In this paper, an imperative study was performed. Based on the previously conducted ND study described in Paper C and Paper D, where the author proved the vehicle data abilities to support the understanding of driver behavior, the holistic idea for real-time personalized support for PA users was proposed. The research question we address in this research is, *"How can vehicle sensors' data be used to convey system design features to ADAS users?"*

To answer this research question, the ability to use PA in various contexts was chosen as a PA feature. The promotion of PA was chosen as a strategy to convey system design to drivers. Afterward, real-time personalized support for PA users was proposed with two key characteristics. First, the presented design of the data-driven communication framework utilizes both historical and real-time data. Historical data enable performance-based categorization of drivers to analyze a driver's need for additional support. At the same time, real-time data help to identify the driving event and evaluate the driving conditions for PA performance in actual time, helping to understand the correct context of interaction between driver and PA. Processing real-time data, together with historical usage data for the identified driver, enables the development of personalized support for that driver. Second, the proposed design aims to provide smart adjustable support by performing a meta-analysis of the driver response to the introduced support strategy, which follows by modifying the communication strategy when needed.

4.5.3 Main results

Personalized driver support in real-time is designed to improve the effectiveness of PA usage. It aims to make drivers reflect on their PA use strategy by informing them about the additional context where PA can be effectively used, helping them identify this context in real-time situations.

To make this support possible, a number of things have to be considered. In this work, we describe the main principle of how this type of support can be organized, design several sequential steps needed to ensure this type of communication, and specify what types of data are needed, and for what purposes.

To address all the issues, the author proposed a design consisting of several sequential steps (see Figure 16). Each step solves a specific task in the course of the design for personalized driver support in real-time.

According to the design of personalized driver support, the driver is not provided with additional assistance in all driving activities. The communication consists of two phases: active and non-active. The active phase is when the driver receives the system's notifications, and the non-active phase provides support-free time when the driver is not guided but uses PA as he/she wants. During support-free time, the effect of previously provided communication is measured, and the need to update the driver category and connected support strategy is evaluated. The conceptualization of the personalized support steps is described in further detail below.

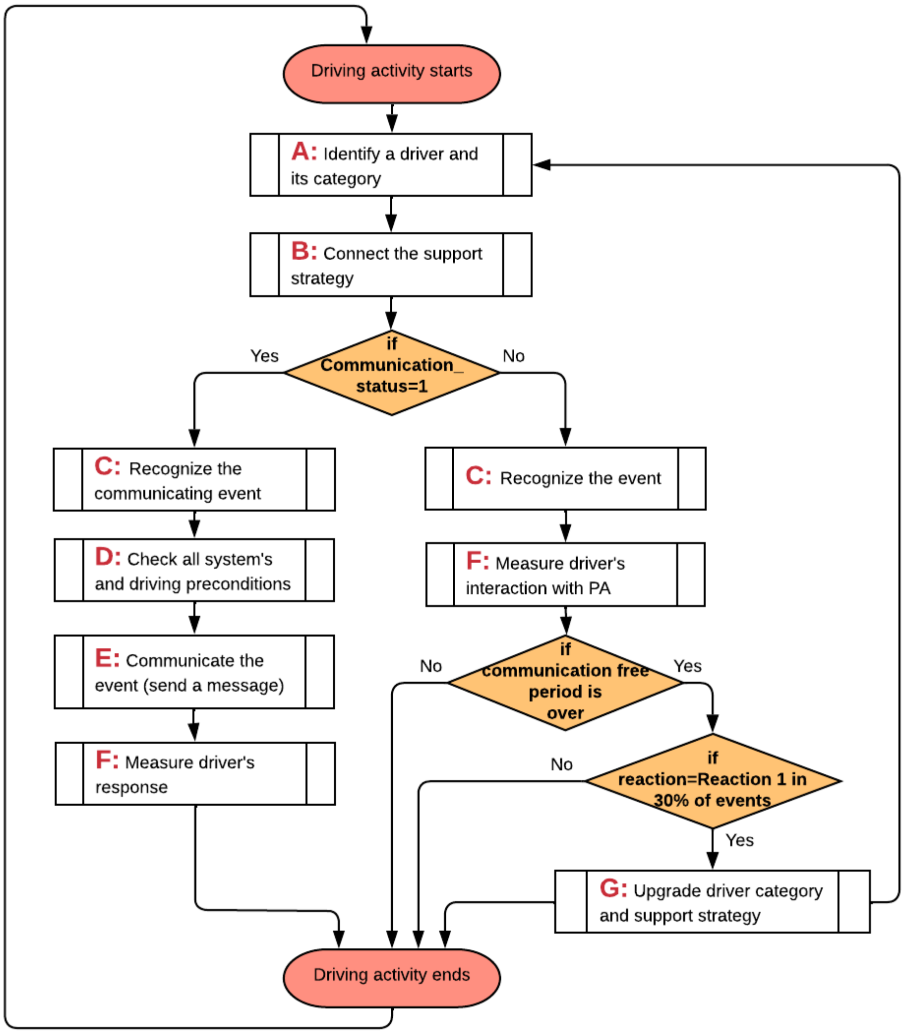

Figure 16. The sequence of steps for real-time personalized support of PA users.

Step A has a two-fold purpose: (1) to identify the driver, and (2) to categorize the driver based on their behavior with the targeted function or system. Since the design aims to provide personalized support, driver identification is critically important to provide functionality. Driver categorization is used to understand driver behavior with the targeted system and to understand in what situations personalized support is needed. In this paper, driver categorization for PA users is based on the extent this function is used and the context in which it is used. Such categorization is connected to the design objectives. Since the design objective is to improve PA usage in different traffic conditions, the behavior in sparse and dense traffic is considered.

Step B decides the communication strategy based on the driver category decided on in step A. Depending on the PA use scenario, the driver receives recommendations on where he/she can improve. If the driver does not use the function at all, the introduction should start from easier tasks or situations and be more explanatory compared to that offered to more experienced users. In situations when the driver uses the function fairly well, the question of how much more the usage can be increased has to be evaluated, especially for non-compulsory systems such as PA.

The communication strategy should not be intrusive or demand too much driver attention. Therefore, the applied logic presumes notifications-free driving activities. This approach would reduce driver distraction and help to evaluate driver learning rate, by monitoring the driver's ability to implement new use strategies without reminders. The driver learning rate is considered in the driver category update and in the change of communicated strategy.

Step C aims to identify the situations where the support should take place. To make this possible in actual driving time, real-time events identification and analysis are required. The paper proposes dense and sparse traffic identification based on the following data parameters: S(l) – speed limit, S(d) – driving speed, R(d) – reaction distance to the vehicle in front, and t – time that condition lasts. Based on how much and in what direction the driving speed differs from the speed limit, and what the distance is to the vehicle in front, the logic decides whether dense or sparse traffic exists. The promotion of PA should happen in accordance with the recommended use of the system since the design cannot promote PA in critical conditions for its performance. This means that the context that is not recommended for PA use should also be identified in step C and excluded from communicated events.

Step D is focused on verifying conditions prior to support message output. For PA specifically, the driving context, related to road and weather conditions, is vital for PA performance. The prerequisites for PA performance require clear lane markings and the absence of a great deal of water, slush, or heavy precipitation since this negatively affects visibility on the road or results in slippery road conditions. Thus, step D uses additional data points that verify the road and weather conditions in real-time and confirm that the conditions for PA promotion are acceptable.

Besides the context, the proposed logic considers the driver's intention to perform the maneuver. Any change of lane, overtaking, turning, etc., is followed by PA deactivation. This means that if it is apparent that one of these types of maneuvers is being prepared for, PA promotion should be postponed until the maneuver is finished.

Furthermore, the related equipment responsiveness should be verified. The cameras and radar system providing PA functionality should be verified to exclude their inadequate response due to mud covering or other reasons.

The number of preconditions checked in step D is highly related to the targeted system, context, and equipment that contributed to the system performance. Promoting another system other than PA could result in a completely different set of preconditions.

Step E is focused on transmitting the support notification to the driver. Thus in this step, it is essential to design what we want to output to the driver, in what form and through what communication channel, so that the support notification becomes understood, timely, and as minimally distractive as possible. Apart from the notification itself, the frequency of communication needs to be considered. If the goal is to constantly support drivers in the context identification, then the communication of context change could be appropriate every time it happens. However, in the case of PA promotion, such behavior could be too persistent, resulting in the neglect of both the support and the function.

When the support takes place, the driver's reaction to this support is important since the design does not imply any direct feedback from the driver due to safety restrictions on secondary interactions during driving. In step F, three different reactions were distinguished: (1) PA was activated in the proposed context; (2) PA was activated but in a different context; and (3) PA was not activated. These reactions need to be understood in real-time, so additional driver behavior monitoring should be in place. Understanding driver reaction is important for the support logic in the next step.

Step G is responsible for driver category and associated support strategy adjustment. The key idea of the proposed support is that the design of the communication is not static but depends on driver reaction and, in the long term, driver behavior change. If the driver consistently follows the support suggestions, the driver category (when passing the set thresholds) will be improved, meaning that the driver will be assigned to a new support strategy, helping him to develop new skills and to try PA in some new context. Depending on the driver's starting category, a series of upgrades might be required before the communication support is discontinued.

Additionally, since the driver is not supported in all driving activities, during the support-free sessions, the driver's behavior is still monitored to see if a driver can recall a previously given recommendation and activates PA in the recommended traffic conditions. The support-free sessions are important when considering the category upgrade since they show that the driver learned and understood support messages and is able to implement this new knowledge without reminders.

Summarizing the above, this paper provides the conceptualization of the idea of personalized driver support for PA. The author describes the idea step-wise, providing an explanation of the details that need to be considered at every step of this personalized driver support design. Additionally, the author describes limitations met during the design phase and discusses how personalized driver support can be further improved in the future.

4.6 PAPER F

4.6.1 Purpose

If Paper E was aiming to conceptualize the idea of driver coaching, the research presented in this paper aims to (1) generalize the coaching approach, making it applicable to the coaching of any in-vehicle system; (2) verify the feasibility of the whole coaching concept, including the applied logic, backend, frontend, data processing and analysis in real-time; and (3) validate the coaching approach through designing and implementing the driver coaching in a practical case study with 20 participants.

4.6.2 Method

First, the imperative study was conducted to generalize the coaching process in the form of a framework design for the Driver Coach process. Subsequently, based on the framework design, the author identified all the affecting factors of driver interactions with Pilot Assist, defined the interaction context, derived the relevant data points to support the coaching process, and designed the coaching process.

Second, the author conducted an empirical study where the proposed Driver Coach design for PA users was verified in terms of applied logic, backend organization, and frontend solution.

Finally, the user study was organized to test the coaching idea on users in the natural environment. An Explanatory Sequential Mixed Methods approach proposed in paper B is adopted in this study. The sequential use of quantitative and qualitative methods aims to facilitate integrated analysis of the PA Coach app's effect on drivers.

The analysis of quantitative data helped in the first place to detect relevant individuals for the study. The driver categorization regarding the level of PA use was performed based on the historical dataset, which includes driving data on more than 3,000 drivers over six months. All drivers were assigned to nine different categories. Driver categorization was made based on two main parameters: the extent of PA usage and the traffic conditions when PA was used. Also, an additional screening process was implemented to exclude extensive sharing of the car or short-term participation.

Quantitative data collection and analysis are used to compare driver behavior before and after the Driver Coach app installation in participating vehicles. The data collection in this study was conducted in two phases: for six months, from April to September 2021, and for four months, from January to April 2022. In the first phase, the PA use behavior was evaluated in order to record the "before" behavior, categorize the drivers, and choose the participants for the second phase. In the second phase, after the PA Coach app was installed, continuous monitoring of PA use behavior for the four additional months was performed to assess the effect of the Driver Coach app on the drivers' behavior.

Qualitative data collection and analysis were performed to validate the quantitative analysis outcome and add the human perspective to the drivers' overall experience with the Driver Coach app for PA. The qualitative study has been designed to investigate the root causes for detected behavioral changes before and after the PA Coach app installation to enrich the data-driven insights with drivers' subjective reflections about it. As a data collection method, extensive questionnaires before and after the study were chosen as a reliable means for gaining knowledge on user behavior, user perceptions, and user satisfaction regarding coaching support. Before the study started, potential participants received a unified set of screening questions, then after the study, according to the applied methodology, all participants received a set of personalized questions that were designed based on individual participant behavior to clarify and verify the data-driven reasoning and dig deeper into the individual issues discovered. Additionally, during the Driver Coach app use period, several feedback sessions were conducted to discuss and capture intermediate drivers' experiences. During these sessions, the participants were encouraged to provide open-ended insights, elaborating on their experiences at the end of each questionnaire.

Subsequently, an integrated analysis of qualitative and quantitative insights was made to measure the Driver Coach app's effect on drivers and their behavior. This effect was estimated from three main perspectives:

1. Measure the increase/decrease of PA usage after the Driver Coach app installation.
2. Evaluate the change in driver behavior use strategies with PA.
3. Assess the perceived usefulness of the Driver Coach app for the drivers.

4.6.3 Main results

As a first part of the results, the framework design of the Driver Coaching process was proposed. The framework consists of four levels, namely Input level, Reasoning level, Output level, and Meta-reasoning level. Figure 17 presents a high-level schematic design for Driver Coach, focusing on what data need to be collected and how they need to be processed to provide an adaptive real-time driver coaching system.

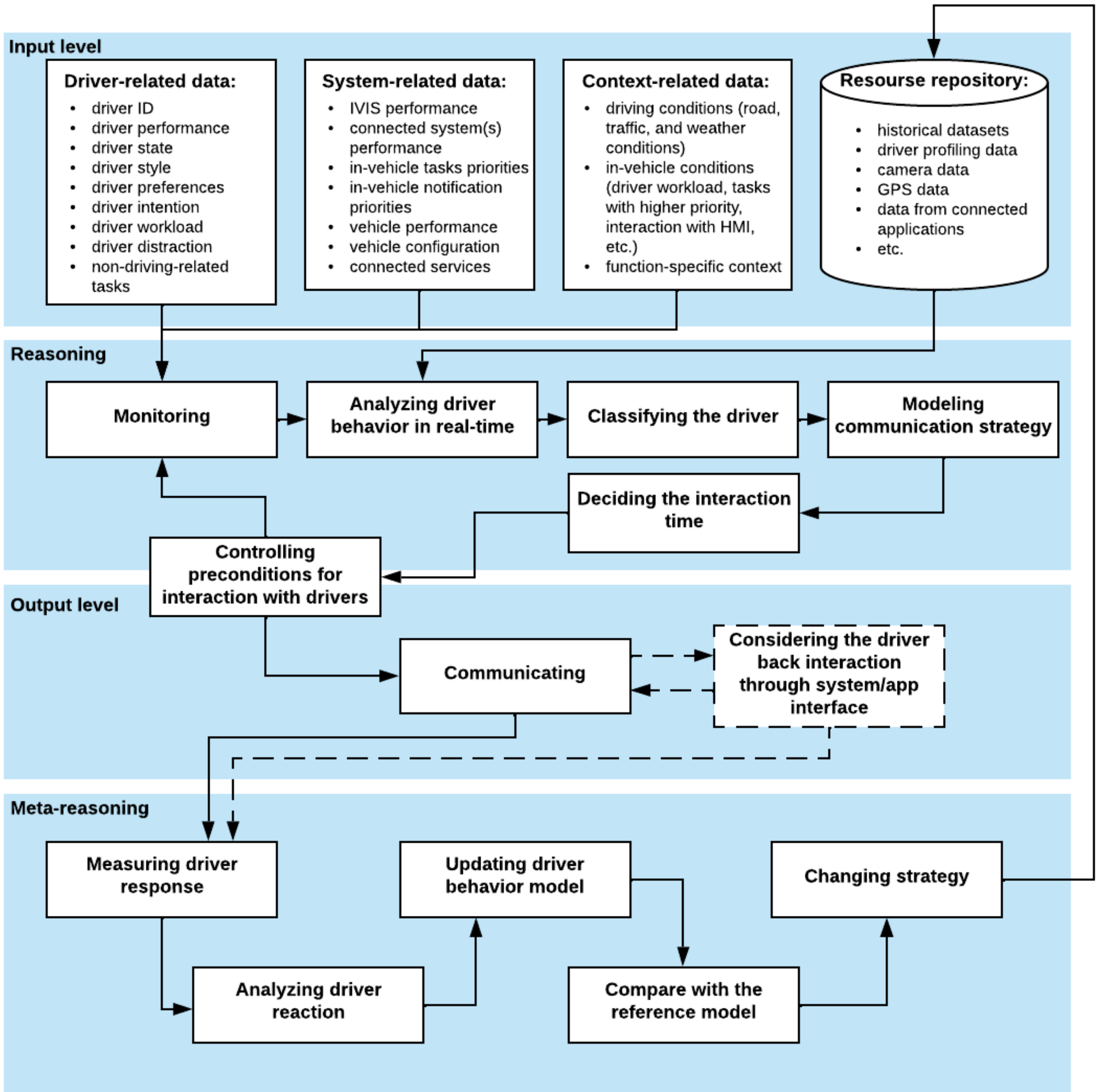

Figure 17. Framework design of the Driver Coaching process.

Based on this framework, the detailed design of the Driver Coach app for Volvo PA was made to exemplify the coaching approach for a specific system. For convenience in the implementation and verification process, the Driver Coach framework, presented in Figure 17, was modified into the modular design, Figure 18. This representation of the framework steps made it possible to dissect a complex design task into smaller parts, facilitating each module's design, development, and testing independently from other modules.

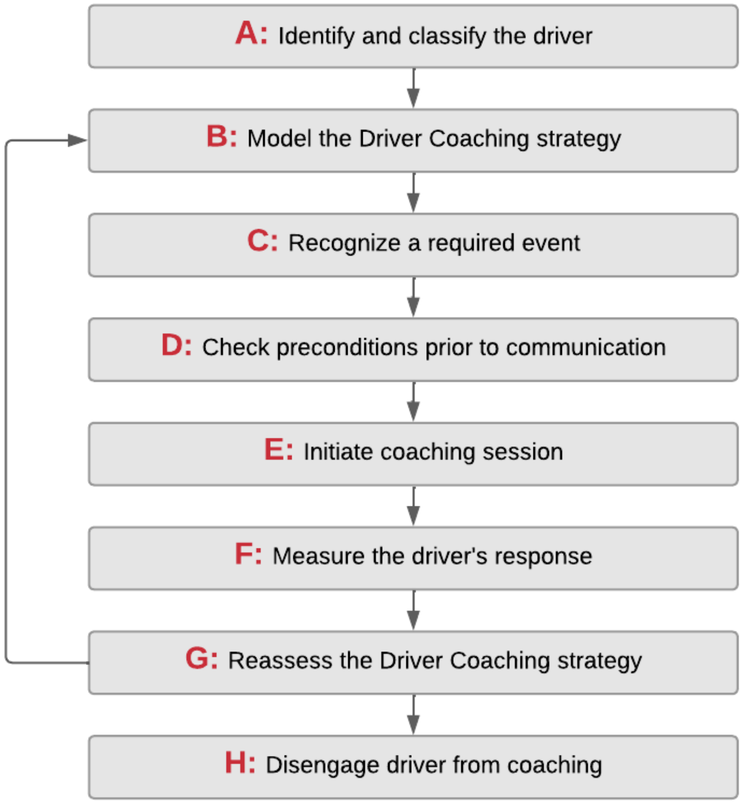

Figure 18. Design of Driver Coach logic modules for Pilot Assist.

When the coaching logic was designed theoretically, the authors verified the logic, and tested backend and frontend solutions based first on the simulator, then on one test car, and finally on all cars before the measurement period started. More of the verification process can be found in Section 5.3.

After the verification process was completed, the measurement process started and lasted four months. The results of this case study showed that the Driver Coach app for PA has an overall positive effect on drivers' behavior with PA. The data shows a steady increase of trips with PA activations throughout the four months, without decreasing the average PA activation duration time per trip. This indicates the rise in PA usage with the Driver Coach application. However, it is too early to conclude regarding the level of improvement. Drivers can further improve since the learning process could still be in place after four months.

The collected data revealed different levels of improvement for different users, showing that not all participants in the study improved at the same rate. Thus, the author observed two user groups with clear commonality in their improvement rates. The first group includes users who improved significantly and showed a higher level of PA use after four months of Driver Coach app usage. The second group contains users who remained on the same PA usage level and haven't shown improvement for the corresponding period. The lack of improvement in the PA use strategy for drivers from group 2 was further explored through qualitative user feedback. The explanations for low/no improvement are the following: (1) drivers do not like the function in general, and (2) it is difficult to grasp the notification since it disappears quickly. If the first reason indicates that the participant is not the one this study should target, then the second reason is more crucial, referring to the messages and logic design. However, the in-depth examination showed that these drivers deactivated the application sound, leaving only graphical representation on the screen. Doing this before the messages are understood and learned is not recommended since it can lead to a poor understanding of the coaching notification.

Furthermore, the drivers' behavior in a critical PA context was explored. Among the positive results, we also discovered that the Driver Coach app might stimulate speeding behavior for drivers who had already demonstrated speeding behavior before. This is critical for the logic design and needs to be verified in the next iterations of the Driver Coach app design. If it proves that the logic stimulates the speeding behavior of some drivers, then the logic needs to be reconsidered, even though it works well for other drivers.

In general, the case study verified the feasibility of the coaching process for such complex systems as ADAS. Driver overall positive reaction shows the potential of this type of driver support. Drivers who want to improve show a significant improvement in the use level of the function and understanding of how the function works and its limitations.

The paper also presents the primary constraints, mostly related to the test environment, and reflects on further improvements that could enhance the coaching support.

4.7 SUMMARY OF THE RESULTS

The results of the appended papers can be summarized as follows:

- The author explored the state-of-the-art of data utilization in the automotive UX design process of in-vehicle systems, giving an overview of data-driven methods and approaches that are used in the automotive sector. The author differentiated between different types of data that can be utilized and compared the digital transformation in the automotive sector to other digital domains.
- The author presented the main limitations of the automotive sector concerning the usage of data-driven approaches and correlated them to the specific needs of UX experts who want to make the UX design process more evidence-based and user-focused.
- Furthermore, the author investigated potential fields of application in which the benefits of the usage of data-driven methods are not yet leveraged and suggested actions for how to better integrate data-driven methods in the UX design process.
- Practicing applied research, the author investigated the ability to gain relevant vehicle data for user-related studies based on one automotive OEM. As a result, the requirements for the data were specified, and the initial dataset was established.
- The limitations regarding vehicle data acquisition and utilization were identified. This included the technical limitations that affect the data feasibility and applicability negatively (e.g., the driver identification in the vehicle) and the barriers associated with sensitive data processing, preventing us from an extensive evaluation of real users in the natural driving environment.
- As part of the imperative study, the effectiveness of qualitative and quantitative methods for user-related studies was investigated. This led to the conclusion that in the areas of system performance, driver performance, and driving context assessments, the use of vehicle data is more efficient. Vehicle data are considered more reliable and trustworthy since they record all interactions with the system and driving environment, compared to the user, who tends to "forget" or generalize certain issues.
- The author also examined the methods used for a driver behavior assessment. The poor integration of qualitative and quantitative approaches leads to the practice where different data types create different types of insights. These insights are often isolated from each other, which makes the synthesis of the results difficult. At the same time, a thoughtful combination of both quantitative and qualitative methods can help to benefit from different data sources.

- As a result of this imperative study, the author proposed a mixed-method approach for user behavior evaluation of ADAS. The method helps to integrate quantitative assessment into the existing qualitative methods, resulting in more precise and comprehensive results.
- The consequent ND study verified the ability of vehicle data to provide insights related to user behavior understanding and showed the advantages of the mixed-method approach in user-related studies.
- Practical implementation of the mixed-method confirmed the effectiveness of this approach, resulting in a more comprehensive context-aware ADAS evaluation, where both driver and system behavior are evaluated in a specified driving context. The quantitative and qualitative approaches in this method complement and validate the results of each other. Thus, according to the author's understanding, this method can result in better trust in the results from industry professionals.
- After the ability of data to evaluate driver behavior to a specified extent was proven, another imperative study was conducted investigating how vehicle data can be used to convey system design features to ADAS users. As a result, the author proposed a real-time driver support system for PA users to improve the effectiveness of PA usage in various driving contexts.
- The idea of the Driver Coach approach was further developed and generalized to the framework for driver coaching.
- Afterwards, the Driver Coach app for PA users was designed and implemented in the subsequent empirical study to exemplify and test the idea of driving coaching. The results proved the feasibility of the coaching process for such complex systems as ADAS and indicated a positive effect of such an approach on drivers.

5

DISCUSSION

This chapter is dedicated to the discussion of the results in connection to the research questions. Additionally, it aims to discuss the quality of the results in relation to the research approach.

5.1 ANSWERING THE RESEARCH QUESTIONS

RQ 1: What vehicle data are relevant to support the understanding of driver behavior?

According to SAE International (2018), the three primary actors in driving with an in-vehicle system are the driver, the system, and the vehicle. Moreover, all interactions between the driver and in-vehicle system happen in a dynamically changing context, which affects both system and driver behavior. Additionally, the vehicle itself is a complex system of systems (SoS) with circulated data that ensure complete vehicle performance. Below, the author analyzes these interrelations in answering the research question of what data are relevant to support the understanding of driver behavior with the in-vehicle system.

Driver behavior has a complex nature, encompassing both subjective and objective understanding of how the user uses the particular system or function in the car. The objective data contribute to understanding what users are doing while performing specific tasks and can be measured objectively through implicit vehicle data in the form of driver performance. However, recorded driver performance is not self-explanatory. To understand driver behavior means to answer the question of why people behave as they do. This part of user behavior was traditionally assessed subjectively. Until recent times, only explicit user feedback collected in qualitative studies with users was used to answer this question. However, with the advances in data-driven technologies, the subjective area has expanded toward objective assessment. Today, the well-detailed quantitative driver behavior insights are a key to a better understanding of drivers' interactions with in-vehicle systems.

Driver-related data

Driver behavior data aim to provide knowledge on the driver's understanding of the system, the effectiveness of his chosen use strategy, his preferences regarding the system use and activation, the ways of handling errors, and other knowledge connected to the set of investigation questions. Driver behavior data also includes driver perception in the form of perceived usefulness of the system, technology acceptance, trust, perceived safety, and satisfaction with the system support since it partially explains why the driver behaves as he does.

Therefore, driver-related data encompass all conceivable data that are possible to extract to answer the set of user behavior questions. At first, for any driver behavior investigation, a driver identification module is required. Driver recognition is a key for driver behavior assessment and any driver-oriented research since it helps to figure out who is operating the vehicle in current driving activity and connect corresponding behavior data to the correct person. Driver identification is also used to separate the behavior data of different drivers who share a particular car, which is extremely important for the retrospective analysis of driver behavior or applications that consider the driver's previous conduct in its logic.

Driver profiling data are another source of driver-related data that keep driving preferences and settings essential for a driver. Depending on the study objectives, these data can contribute to understanding the preferred settings for navigation, audio and media systems, language and voice control, and other parameters added and kept in profile.

Second, driver performance data are required. Performance records should be detailed enough to understand not only the final result in the form of function status change but also the instruments the driver uses and the ways he uses them to achieve this result (choice of interface, sequence of performed steps, uncompleted operations, errors that lead to poor system response, and other related metrics). This level of detailing gives much more information about the driver's understanding of the situation, his intention, and how this intention is forwarded. For example, if the driver deactivates PA by changing lanes, it indicates his indirect intention to deactivate PA. But if the driver used the PA interface to deactivate PA, it is a direct intention. This type of data could be relevant for specific questions on driver behavior. The level of detail for performance data should be derived based on the study objectives.

If the performance data show what the driver did, then the data on what the driver is going to do help to foresee and optimize system behavior considering driver intention. Driver intention's indicators are essential, especially for automated support systems that monitor driver behavior in real-time to provide relevant support. Driver intention metrics could be based on simple data points processing, such as the turn indication showing that the driver is preparing to maneuver. However, the more complex AI-based frameworks that focus on predicting driver behavior based on the historical evidence on specific behavior also exist.

Further, the driving style, which is the way the driver behaves in a particular trip or situation, could be relevant for driver behavior evaluation. The driving style could be characterized as, for example, aggressive vs non-aggressive, active vs passive (concerning steering), driving with automation vs self-driving, amongst others. In its turn, the driving style could depend on the driver's current state and surrounding context. Therefore, the driving style and driver state could be relevant for frameworks that aim to correct driver behavior.

Furthermore, data indicated driver distraction and workload contribute to further understanding of driver behavior and help, for example, optimize the distribution of the tasks to reduce driver workload or explain low driver responsiveness to the system notifications. In contrast to driver performance data, driver distraction and workload knowledge might not be relevant to all driver-related studies. Still, it adds value if applicable to the investigated objectives.

Table 1 presents the summary of driver-related data that can be considered for driver behavior evaluation.

Table 1. Summary of driver-related data.

Driver-related variables	Description
Driver identification	The key for any driver-focused research; helps to figure out who is operating the vehicle in current driving activity and connect corresponding behavior data to the correct person.
Driver preferences	Driver profile data keeps driving preferences and settings essential for a driver. Can contribute to understanding the preferred settings for navigation, audio and media systems, language and voice control, and other parameters.
Driver performance	Records related to driver's choice of interface, sequence of performed steps, uncompleted operations, errors that lead to poor system response, and other related metrics. Driver performance helps better understand the situation, driver's intention, and how this intention is forwarded. It is important to distinguish driver performance from any actions performed by the passengers.
Driver intention	Helps to foresee driver behavior and optimize system behavior considering driver intention.
Driver workload	Driver workload includes both physical and mental workload that results from multiple tasks performance provided by external or internal context. Understanding of driver workload helps to optimize the distribution of the tasks and/or notifications.
Driver distraction	Such activities as talking to the passengers or listening to music contribute to driver distraction. Driving distraction metrics helps to optimize the distribution of the tasks or explain low driver responsiveness to the system notifications.
Driver style	Aggressive vs non-aggressive (concerning braking/acceleration), active vs passive (concerning steering), driving with automation vs self-driving, or others. Driver style could be relevant for studies that aim to correct driver behavior.
Driver state	Relaxed, nervous, sleepy, tired, etc. Driver's current state affects the way they behave and could be relevant for frameworks that aim to correct driver behavior.
Driver's eyes and hands positioning	Driver monitoring system or vehicle internal sensors can help to find out where the driver is looking and whether his hands are on the steering wheel. These metrics are vital to understanding and modeling driver behavior.
Non-driving related tasks	Tuning of interfaces, search in the HMI, changing the destination point in the navigation system, or other activities contribute to driver workload and driver distraction, and need to be considered for comprehensive driver behavior understanding.

In general, driver-related data are not well designed compared to system-related data. Therefore, the contribution of different data sources often helps organize datasets with a good level of detail. The better user-related data are detailed, the easier it would be to understand how interrelated factors affect driver behavior. However, the choice of data types and metrics should be connected to specific research questions set individually in each study, since the more data is linked, the more time-consuming and complex the analysis becomes.

Context-related data

By driving the vehicle and being inside it, a driver creates two types of contexts: external and internal contexts. External context, or driving context, describes the situation outside the vehicle. The driving context could be described as the summary of external factors that affect driver behavior while using the evaluated system (Zhai et al., 2018) and defined as the aggregation of traffic, road, and weather conditions that, in association, can encourage or discourage driver interactions with in-vehicle systems. In contrast, internal or in-vehicle context refers to the driver's activities inside the vehicle. The in-vehicle context, such as listening to music or talking to passengers, can also be relevant for the moment of driver-system interaction since it indicates the driver's state and workload.

The context is system-dependent. Therefore, it should be defined depending on the function in focus. For example, if system performance deteriorates in poor weather conditions, the weather condition should be a part of the context. But if the system performance is independent of weather changes, the inclusion of weather conditions in the context description will be redundant.

Including detailed context assessment through implicit data helps understand driver behavior as a reaction to context change. The context, of course, does not cover all possible reasons for driver behavior changes but contributes to the understanding of how a particular context changes the behavior. And according to the Paper C results, the effect of driving context on driver behavior is proven and documented. Table 2 presents the summary of context-related data that can be considered for driver behavior evaluation.

Table 2. Summary of context-related data.

Context-related variables	Description
Road conditions	Part of driving context, related to the road infrastructure; usually static and represented by road markings and road signs.
Weather conditions	Part of driving context; affects different systems' performance and requires special actions from drivers, such as turning on fog lights or wipers.
Traffic conditions	Part of driving context that has biggest impact on driver behavior due to its dynamically changing nature, and that requires high driver attention in situations with dense traffic.
System-specific context	If system works under specific conditions these conditions become part of the system related context and have to be considered in driver-system interactions analysis.
In-vehicle context	For example, presence of passengers, talking, listening to music, etc.

Data supporting the external context assessment improves fairly quickly since driving context recognition is a part of autonomous driving research, and OEMs compete in the speed that autonomous vehicles are entering the market. In contrast, data supporting the in-vehicle context understanding is poorly defined and explored. However, despite the reduced data availability to support its monitoring, in-vehicle context contributes to understanding driver distraction, driver state, or workload at a particular moment. This helps to better understand the driver's behavior and needs in a specific moment and provide additional support to the driver if this is the goal in a particular study.

System-related data

Defining the system-related data, one should understand that none of the vehicle systems can be seen in isolation. The vehicle is a system of systems (SoS) where the data are circulated to ensure the whole system's performance. The output from one system could become the input for another and contribute to performance or enable a third functionality. These interdependencies between internal systems need to be understood and considered while planning the data collection or defining the context for the targeted function.

System-related data usually encompass targeted system performance, the performance of related systems, vehicle-specific configuration, and connected services that support, automate or enhance driver behavior with the targeted system. Table 3 presents the summary of system-related data that could be used if related to the targeted system or behavior change.

Table 3. Summary of system-related data.

Vehicle/system variables	Description
Targeted system performance	Performance of the system under evaluation.
Related system(s) performance	All systems' performance that affects or contributes to the performance of the targeted system.
Related vehicle performance	It could be essential to evaluate driver-targeted system interactions only when the vehicle is moving. In this case, it creates additional context related to system performance.
Vehicle configuration	Vehicle configuration predefines the functionalities that a particular car has, the interface realization, and the level of automation. This predefines a driver's possible behavior.
Connected services	All services and apps that are used and relate to driver behavior with the targeted system should be part of the overall context.
In-vehicle tasks priority	Could be relevant for systems that plan and provide support to the driver.
In-vehicle notifications priority	Could be relevant for systems that plan and provide support to the driver.

System-related data are extensively represented in current vehicles. Nevertheless, work should be focused on deriving the most relevant data point from the list of those available since multiple data points from different systems could be available for a single parameter.

Driver behavior data used in this research

This research was focused on ADAS function, Volvo PA and ACC specifically, and was based on one specific automotive OEM. Therefore, the author illustrates how the theoretical vision for what data are needed for user behavior understanding with PA and ACC was applied in this research. The author describes what driver behavior data were derived for the project, what limitations to data collection were encountered, and how they were addressed in the studies.

One of the most significant limitations of driver behavior datasets in conducted studies is the absence of data points for driver identification in the vehicle. Although a theoretical framework for driver identification through indirect signals was proposed (Orlovska et al., 2019b), it was not tested or verified in practice. As a result, the driver behavior datasets of the studies did not support the car-sharing concept. If, for example, two drivers that share the vehicle have entirely different use strategies regarding the evaluated system, the cumulative behavior will represent neither of the drivers. This limitation resulted in a constraint to the study design. Only the sole driver of the cars or drivers who share their vehicle to a limited extent were invited to participate in the studies.

Furthermore, driver performance described driver interactions with PA and ACC were measured. The interface for these functions is relatively simple. There was no need to monitor the way or the sequence the driver used to activate one of these functions since there is the only way to start ACC and PA through its interface. However, the deactivation of these functions could be performed in multiple ways. Apart from the PA/ACC interface, the driver can change lane, overtake, pass a crossroad or implement active steering. One of these actions would be enough to change the status of the functions from active to standby mode. One limitation of our design is that we count these deactivations without understanding if they were part of the driver's real intention or resulted from the context change.

The only driver intention that was considered relevant and was part of the Driver Coach framework for PA (**Paper F**) was the driver's intention to perform a maneuver. The promotion of PA cannot be made when the driver plans to change the lane, overtake, turn, etc., since these types of maneuvers will be followed by PA deactivation. Understanding the driver's intention to perform a maneuver made the PA promotion more accurate, allowing postponing the coaching notification until the maneuver is finished.

Driver style is connected to driver classification implemented in the Driver Coach app for PA – driving with automation and manual driving – since it is related to the study objectives to increase driving with ADAS. Using automation contributes to safer driving since PA implements a "driving in-the-flow" strategy without changing lanes or overtaking. In contrast, manual driving is usually harsher in braking/acceleration, or when the driver implements active steering depending on his current mood or state.

Since PA does not perform equally well in all driving contexts, due to the technical limitations of this function, in order to evaluate driver behavior, all context parameters affecting ADAS performance need to be considered. Weather conditions for stable performance presume monitoring and controlling during heavy precipitation and mist that affect visibility on the road. Stable road conditions require clear lane markings and the absence of slippery road conditions, which is a combination of weather and road conditions. Additionally, using PA in residential areas is not recommended. The author also connected this limitation to road conditions since the speed limit sign of 30 km/h describes the road type that the driver uses. As for the ACC function, it provides only a part of PA functionality, namely longitudinal control. Therefore, it does not have different context parameters from those described above. When all related weather and road conditions were identified, the author set specific thresholds that help to distinguish critical conditions from acceptable ones.

As for the system- and vehicle-related data, the following data were added: PA status change monitoring, ACC status change monitoring (since it is a part of the PA functionality), the metadata on vehicle configuration (year of production, model, engine type, etc.), equipment responsiveness for camera and radar system, and the app responsiveness in the study from **Paper F**.

Finally, based on the research purposes of the study in **Paper F**, which is to promote the use of the PA in various traffic conditions, the data points for traffic situation identification were added to the overall dataset. Based on different traffic situations identified in real-time, the Driver Coach app provides personalized recommendations to drivers.

As demonstrated in this research, the vehicle data can support the complex assessment of driver-system interactions, considering the spectrum of contextual factors affecting these interactions. In particular, vehicle data can support the measurement of both the driver and system(s) performance, as well as contextual information such as the weather conditions, the road conditions, and the data indicating the traffic conditions on the roads. The summary of the measured variables for ADAS evaluation is presented in Table 4.

Table 4. Summary of data variables used for the ADAS evaluation.

Driver-related variables	Description
Number of DCs	per day/week/month to understand the level of activity
Time of DC start	number of activations within one single DC
Duration of DC	to understand the type of trip
Frequency of PA/ACC usage	to count activations within one DC
Duration of PA/ACC usage	to calculate the activation duration for PA/ACC
Time of act./deact.	to understand the type of trip
DC length	to understand the type of trip
DC type	to understand the type of trip
Turn indication	to foresee driver intention to perform a maneuver
GPS location	to map driver behavior to the driving context in the zoom-in analysis

Context variables	Description
Wiping status	to detect heavy rain or snow
Fog illumination	to control visibility on the road
Ambient temperature	to exclude slippery road conditions
Lane marks reading	a precondition for ADAS performance
Speed limits	to identify the road type
Driving speed	to see the deviation from speed limits
Braking/Acceleration	to determine the distance between changes
Distance to the vehicle in front	to identify heavy traffic
Vehicle/System(s) variables	**Description**
ACC performance	on/off/standby mode – contributes to PA performance
PA performance	on/off/standby mode
PA availability	the signal tells you if LatCtrl is OK to activate
Radar On/Off	the signal from the radar ensures ADAS performance
Camera On/Off	the signal from the cameras ensures ADAS performance
Coach App response	the signal that returns true/false connection value in every DC
Vehicle Metadata	model, market, year of production, vehicle-specific configuration, etc.

These data offer the possibility to determine individual user behavior, and to describe, categorize and compare this to the average within a group. Furthermore, vehicle data analysis enables understanding of the severity of detected issues by checking the number of vehicles or DCs that accounted for the same problem. All of those mentioned above provide the ability to effectively apply quantitative research methods that focus on detecting and investigating driver behavior patterns.

Moreover, vehicle data acquired from the ND studies is the only way of unobtrusively logging the interrelations between the system and the human in a real driving environment. In general, the ND data analysis allows precise and reliable results to be obtained since the outcomes are based on statistical methods and can always be assessed with regard to their statistical significance.

However, it is essential to acknowledge that the vehicle data are not perfect and need further development. The described limitations prevent more efficient use of vehicle data. Since data availability is continually improving, the dataset representing the driver and context parameters can be further improved. For example, the effect of the oncoming traffic or the in-vehicle context (the use of a mobile phone, distraction from passengers, etc.) was not extensively assessed due to the technical feasibility and GDPS legislation regarding establishing these signals. Thus, vehicle sensors and means of internal context assessment, such as camera-based driver monitoring for a better understanding of in-vehicle context, need to be continuously improved to provide a more detailed understanding of driver-system interaction.

RQ1 was considered a primary research question since most limitations and technical constraints were met at the beginning of this research and followed until its end. Therefore, all studies focused on building up and further improving the comprehensive dataset required for user-focused studies. Practicing applied research helped reflect how currently missing data could improve driver behavior assessment in the future. In **Papers C & D**, the author designed the dataset and performed a full-scale evaluation to illustrate the ability of vehicle data to contribute to driver behavior understanding. Based on the proven ability of vehicle data to understand driver behavior in a specific extent, **Paper F** presents the design for real-time data processing, which also finished with satisfying results despite the applied limitations. Finally, **Paper A** presents a summary of current limitations that restrict a data-driven approach in different automotive OEMs and provides recommended actions to improve data availability for user-focused studies.

RQ 2: How can the data-driven approach be incorporated into existing methods for driver behavior evaluation?

Today, no single method can support the evaluation of the whole complexity of driver interactions with ADAS. The traditional way of driver behavior evaluation, solely based on subjective user feedback, cannot consider all interrelating factors between the driver and the system in a dynamic driving context. At the same time, there is no systematic approach regarding the utilization of vehicle data. Vehicle data are extensively used for system performance verification but less used in driver behavior evaluation and driving context assessments due to their limitations. Therefore, in **Paper B**, the author proposed the explanatory sequential mixed-method approach, aiming to effectively utilize both quantitative and qualitative data types to comprehensively assess driver behavior in relation to complex systems akin to ADAS. Subsequently, **Papers B, C, D & F** implemented the mixed-method design in data analysis, validating the method design through practical application.

The explanatory sequential mixed-method design proposed by the author aims to improve the quality of driver behavior assessment by combining quantitative and qualitative methods in the most effective way, overcoming the limitations of quantitative data with the benefits of qualitative data and vice versa. However, a simple merging of results does not always lead to the achievement of a comprehensive understanding of investigated phenomena. The data are usually different in nature and structure because the qualitative and quantitative studies are designed with a different focus and aim to explore various aspects of the same problem. In practice, the results are often not synchronized, are incompatible and difficult to use (Orlovska et al., 2020). Therefore, the sequential use of both methods allows us to build an in-depth qualitative investigation using the insights of the quantitative study. The topic of interest can be chosen or added after the results from the quantitative evaluation are obtained if, for example, some interesting pattern in driving behavior is identified.

In the mixed-method approach, the qualitative study design is a way to explain quantitatively detected issues. Thus, the focus of the qualitative investigation, the choice of participants, and the design of the questionnaire should be made based on the results from the quantitative evaluation. During the qualitative study, different participants could be asked various questions based on their recorded behavior and with the aim to explore the reasons for this behavior. This personalized approach is more effective than the standardized questionnaire, where the participant could be asked about specific behavior or situations that he has never encountered.

Additionally, the mixed-method approach contributes to higher compatibility of the results between studies since the objectives of one study are based on the metrics from another.
Finally, the sequential mixed-method approach helps to cross-validate the results of both studies and evaluate the completeness of their datasets by reflecting on the missing knowledge in the overall assessment. This allows, for example, the ability to assess if the identified fragmented issue from the qualitative investigation is significant for the whole pool of participants or, based on qualitative study output, discover new insights beyond the quantitative results covered by the initial quantitative analysis.

RQ 3: How can vehicle data be used to support users' adaptation to smart in-vehicle systems?

First in this research, the author understood what vehicle data are needed and how they can be used for a driver behavior evaluation. Several practical studies verified the data's ability to reveal knowledge regarding driver behavior, making the author think about new applications for behavioral data utilization that enrich the design of smart in-vehicle systems.

The problems with understanding related to low trust or over-trust in the technology (Itoh, 2012; Kazi et al., 2007) due to poor understanding of ADAS capabilities and limitations (Llaneras, 2006; Jenness et al., 2008; Aziz et al., 2013) helped to formulate what type of smart support is needed to achieve better understanding and acceptance by ADAS users.

At the same time, research has shown that providing feedback is a powerful tool for stimulating a behavior change (e.g., Fischer, 2008; Allcott and Mullainathan, 2010; Stern, 2011). Today, in-vehicle feedback technologies are able to provide drivers with real-time, performance-based feedback on their behavior, implementing different driver behavior optimization algorithms. Feedback on how to optimize helps to gain confidence, decrease the workload, or better understand the technology, resulting in the more conscious use of such systems as PA.

Motivating people to use automation effectively can be considered a learning process. Feedback is an essential component of learning, and its principles are rooted in educational theory (Darby, 2001). Receiving feedback can be an important part of the learning process, helping drivers learn new skills and hopefully form new habits (Brouwer et al., 2015).

On the other hand, drivers vary considerably. They have different previous experiences, attitudes toward automation, preferences, and habits. Depending on their individual experience, the learning process can take different times. For example, the study by Trübswetter (2013) showed that older adults are slower to learn and adapt. Therefore, drivers require custom-made solutions to explain how their particular driving behavior can be improved (Gonder et al., 2011). This is in line with He et al. (2010), who argued that a unified way of presenting feedback to differently motivated drivers might not be that effective, saying that consideration of specific values and goals of each individual when providing feedback to drivers is essential. Thus, the research community indicates a need for personalization that considers driver needs, previous experience, and current level of technology understanding. Personalization could be achieved by, for example, categorizing drivers regarding their behavior and implementing the reasoning and meta-reasoning process (Gilman and Riekki, 2012).

Therefore, the designed Driver Coach framework encompasses the ideas expressed by the research community and provides a description of a general process of driver coaching.

Driver Coach framework design (see Figure 17) is unique in combining the following five essential characteristics:

1. Performance-based drivers' categorization regarding targeted function or system use.
2. Real-time driving event and driving context recognition.
3. Implementation of several driver support strategies based on driver behavior analysis in various contexts.
4. Personalized communication based on the driver's use strategy with the targeted system.
5. Meta-analysis of the driver response to implemented strategy and adjustment of the communication strategy when needed.

Subsequently, the general Driver Coach framework became a basis for designing real-time personalized coaching support for PA users. The Driver Coach app for PA users aims to: (1) promote PA in different traffic situations to increase the general use of this type of semi-automation; (2) improve driver experience regarding PA usage by better explaining system performance and its limitations; (3) provide help in the navigation through the PA interface; (4) support with both suitable PA use context and critical context when the PA performance can deteriorate.

The Driver Coach app for PA users is based on real-time telematics data obtained from vehicle CAN and FlexRay busses to monitor driver behavior and understand the need for driver support for the specific user. Furthermore, constant controlling and monitoring of driver behavior helps in gathering understanding regarding driver response to the provided support and reasoning about how well the PA Coach app strategy fits a particular user's needs.

The Driver Coach app design includes reasoning and meta-reasoning levels. On the Reasoning level, modeling the correct strategy for the user occurs. The Meta-reasoning level aims to understand the effect of coaching on the driver by analyzing a driver's response to provided support notification. This analysis helps to adapt the support strategy and optimize the interaction strategy with the driver when needed. Thus, depending on the driver's reaction to the provided support, the meta-reasoning reassesses the currently applied logic and decides the next communication time and frequency of these communications.

In summary, the author designed (Figure 19) and tested a new smart service, namely Driver Coach for PA, demonstrating that vehicle-based driver behavior data can be used as a source for add-on services to existing functionality. This approach is applicable for design support for any vehicle system and could be especially useful for introducing novel vehicle systems to drivers.

Figure 19. Front-end design and implementation for Driver Coach app for PA.

5.2 CLARIFICATION OF RESULTS AND SUCCESS CRITERIA

Many factors influence research success. According to the DRM, there are no established metrics to measure success. It is suggested to set the measurable success criteria that are linked to the research goals. The term "measurable" refers to the possibility of evaluation criteria during the research project, i.e., mixed methods can be used in this case (Blessing & Chakrabarti, 2009). In this research, the *Success Criteria* related to the research questions were set as follows:

- Possibility to define the vehicle data needed for a data-driven driver behavior assessment.
- Ability to handle vehicle data in the driver behavior assessment.
- Ability to design and implement a methodology capable of assessing driver behavior for the system under evaluation based on vehicle data.
- Possibility to implement and demonstrate the ability of the proposed method to improve the quality of the evaluating processes in one or few parameters.

- Proposing a novel approach for vehicle data utilization in the smart user-focused design of vehicle systems.
- Possibility to prove the positive effect on driver behavior of implementing such an approach.

Consequently, the *Fulfillment and Measurability of the Success Criteria* are expressed as follows:

- The interrelated factors for driver behavior assessment were investigated, and all relevant data that contributes to driver behavior interaction with the targeted system was derived and grouped as the driver-, system- and context-related data.
- The feasibility of driver behavior data extraction was practically tested in multiple studies based on one automotive OEM. Nevertheless, the results were correlated to the existing practices in other automotive OEMs (**Paper A**) to show the similarities in current data development. Most automotive OEMs have similar limitations regarding data availability derived in the course of this research.
- **Papers C, D & F** perform driver behavior evaluation, proving the ability of vehicle data to enable conclusions regarding driver behavior and describe the extent to which vehicle data can contribute to driver behavior understanding.
- The mixed-method approach designed for comprehensive driver behavior understanding was practically verified in studies documented in **Papers C, D & F** and revealed several benefits for driver behavior evaluation: (1) higher compatibility between quantitative and qualitative results; (2) more comprehensive evaluation since most of the limitations of quantitative data could be covered by possibilities of qualitative data and vice versa; (3) decrease of time and resources on the design of qualitative study and choice of relevant participants; (4) possibility to implement the personalized approach in the qualitative study, based on recorded behavior, for each participant; (5) higher validity of results due to cross-validation of subjective and objective data.
- The Driver Coach support was designed as a personalized context-aware approach that helps drivers to navigate the system and supports learning of the system's abilities and limitations in the natural driving environment. This approach enhances the existing system design with the smart add-on to improve the driver-system interactions with the targeted system.
- The Driver Coach approach was implemented for PA and tested in a practical study (**Paper F**) with real users. The results showed the following positive effects for different users: (1) an increase in general usage of PA; (2) a better understanding of the PA abilities and the expansion of use context for PA; (3) a better understanding of PA limitations and decrease of PA use in PA critical context.

Since data-driven development in the automotive sector is rapidly improving, the author expects better availability of vehicle data shortly. This will increase the quality of Driver Coach and improve the proposed method by overcoming the current data limitations. Furthermore, since the study described in **Paper F** is a pilot study, further rounds of improvement of the proposed methodology are needed before being adopted by the industry. Several industrial studies need to be conducted to further test the efficiency of the Driver Coach approach.

5.3 VERIFICATION AND VALIDATION

In order to establish a good quality of research, it is important to verify and validate the results. The verification of the results can be ensured by *Logical verification,* which entails the analysis of *coherency*, *completeness* of the results, and *consistency* of internal and external elements.

Validation by acceptance focuses on the acceptance of new scientific contributions by the scientific community and industry experts within the field.

5.3.1 Logical verification

Coherency is understood as the agreement between established methods and theories. In this research, the author ensured *coherency* by constructing the method's elements from previously applied research. The achieved results and findings demonstrate *completeness* if they fit into the established theories. The *completeness* of this research is verified by following the steps and guidance of the applied research methodology. *Consistency* is achieved if there are no conflicts in terminology or between different research theories. The current research is based on a combination of established research approaches. The results were always compared to the research publications within and outside the field, which ensured the *external consistency* of this research. Moreover, co-authorship with authors from different areas and research groups supported the terminology and glossary verification. Regarding the *internal consistency*, no conflict elements were observed in this research.

5.3.2 Validation by acceptance

A mixed-method approach has been applied in this research. The validity of this type of research needs to be discussed from two different perspectives: quantitative and qualitative.

Validity in quantitative research

Validity in a quantitative study is defined as the extent to which a concept is accurately measured. According to Heale and Twycross (2015), there are three major types of validity: *content validity*, *construct validity*, and *criterion validity*.

Content validity concerns the correctness and accuracy of measurements determined to assess the phenomena. In this research, industrial professionals validated all datasets designed for the studies. The signal descriptions and the correctness of signal outputs were discussed before the measurements started and after achieving the first prototyping results. Further, each dataset collected for different studies went through a data quality assessment. The data quality dimensions, such as accuracy, consistency, timeliness, uniqueness, and others, were used to ensure the quality of recorded data.

As a part of the content validity, the author also verified the dataset's completeness, evaluating if this data can provide information regarding all set objectives. Some complex metrics, based on indirect data processing, were validated in isolation before using them in more complex logic. The tests were first conducted based on the simulator, then on one test car, and consequently on the pool of vehicles.

Construct validity is the extent to which a research instrument (data acquisition system in this research) measures the intended construct. *Construct validity* refers to whether one can draw conclusions about test scores related to the studied concept. Despite the data acquisition system used in the performed studies belonging to the industrial partner and validated internally at the company, this research revealed a few limitations related to consistency and completeness of data collection. In these cases, the author carefully drew conclusions and always described the boundaries so that the reader understands what limits the conclusions drawn.

The construct validity also required logic verification. The set values of thresholds for event identification were verified based on simulator tests and validated with real users, ensuring that the established rules and thresholds identified events correctly according to the initial logic design.

The final measure of validity is *criterion validity*, the extent to which a research instrument is related to other instruments that measure the same variables. The *criterion validity* in this research was assessed based on a literature review within the same field. ND studies and the description of variables they measure, as well as the results they achieve, correlate with the data used in this research and the results achieved.

Validity in qualitative research

To ensure the validity of research elements in qualitative research, three main aspects need to be discussed: *internal validity*, *external validity* and *construct validity* (Winter, 2000).

Internal validity ensures the validity of the results within the study. This internal validity aspect was considered by designing a number of pre-studies where the prototyping results were delivered and analyzed together with the industrial partners responsible for the quality of data delivery.

External validity concerns the generalizability of the results. This aspect was approached by the deliberate choice of measurement parameters, which are quite broad (e.g., different types of vehicles, the extensive range of users, a variety of vehicle models, and different markets). This approach helps to achieve a broader understanding of the ADAS functions and contributes to the generalizability of the results. A comparison of results across the OEMs was performed in the study described in **Paper A**, where authors from different research areas (UX and data-driven development) and different automotive OEMs in Germany and Sweden (Daimler, Volvo Cars, and Porsche) compared numerous independent findings. This study comprised two interview studies with more than 15 UX practitioners, and two action research studies conducted with two different OEMs. Based on these results, the authors agreed on and synthesized the need for data support, extracted limitations within the automotive sector that hinder the application of data-driven methods, elaborated on unleveraged potentials, and formulated general recommendations to improve the usage of vehicle data.

Construct validity establishes correct operational measures for the concept being studied. To achieve contract validity in studies described in **Papers C, D & F** that involve qualitative data collection and analysis, the qualitative researchers were invited for co-authorship. The main purpose was to maintain the correct structure of the study design, verify the data collection tools and methods, ensure the correctness of the coding approach, and validate findings by correlating quantitative findings and themes from the quantitative data evaluation and qualitative user study. Thus, the use of structured coding techniques correlates with the presented descriptive information associated with the collected data, and the cross-validation of quantitative and qualitative results in this study increases the validity of overall results.

Additionally, different methods for qualitative data analysis were used to consider the user input before, during, and after the studies. The combination of such qualitative methods as screening questionnaires, semi-structured interviews, and self-assessment forms helped in verifying the compliance of the identified trends derived quantitively.

Cross-validation

As was previously mentioned, a cross-validation approach was implemented in studies described in **Papers C, D & F**. The drivers' interview insights were cross-validated with quantitative findings, and the correlation of the results was confirmed. Moreover, industrial professionals cross-validated both quantitative and qualitative insights by reviewing publications before publishing. All published papers had been granted permission from the OEM to be published

Additionally, the intermediate and final results were presented numerous times to the industrial partners. The involvement of people with different expertise in these discussions helped address their feedback in the early stages and, therefore, increased the quality of the applied research approach and presented outcomes

Finally, all papers included in this thesis have undergone the peer-review process, where international academics agreed on the quality of provided methodology and presented results, which resulted in acceptance for journal publication and international conferences.

5.4 RESEARCH CONTRIBUTION

5.4.1 Scientific contribution

One of the scientific goals of this research is to design a method for effective user behavior evaluation utilizing vehicle data, and to understand how this method can be incorporated into the existing practices of user behavior evaluation. According to these goals, the following steps were carried out:

- The author designed a novel methodology for vehicle data utilization, defining the area where vehicle data can be used, identifying the influencing factors for the evaluated objects, and defining the relevant data for the evaluation of data-driven driver behavior.
- Furthermore, since no single method could help capture the complexity of user behavior due to a combination of qualitative and quantitative disciplines, the development of the mixed-method approach designed as a next step effectively combines quantitative and quantitative data analysis and helps to handle the complexity of driver behavior evaluation considering the context of interaction.

Another scientific goal of this research is to learn how to utilize the gained knowledge regarding driver behavior in designing smart systems or services to enhance driver interaction with the targeted system. According to this goal, the following steps were carried out:

- The author proposed the design for driver support in the form of a Driver Coach framework, describing the data needed for this type of support and general principles that enable context-aware driver coaching in a natural driving environment.
- Further, the author presented a detailed design of the Driver Coach app for Pilot Assist to illustrate the applicability of the Driver Coach framework to any system and verify the designed method.
- The author also carried out a practical study to further verify the designed method, prove the possibility of real-time driver behavior assessment, test the technical feasibility of the coaching process, and measure the effectiveness of the Driver Coach app on drivers.

5.4.2 Industrial contribution

The results contribute to industrial practice by enhancing the quality of driver-system interactions with ADAS. The main industrial goal of this research project was to learn how to utilize vehicle signals in user-related studies and transfer this knowledge to the engineers dealing with these types of tasks in practice. The results of this research were documented and transmitted to the OEM in a comprehensive report on the research project, where the data-driven evaluation's possible implications, advantages, and limitations were described. During this research, the author constantly set new requirements for data points for driver behavior understanding, which stimulated the development of user-related data. Moreover, the author continuously worked with data quality assessment, improving the existing quality of data acquisition and data pre-processing.

The designed mixed-method approach was successfully tested in three industrial studies **(Papers C, D, and F)** and showed an increase in the quality of the driver behavior evaluation due to an effective combination of different types of data and data analysis. The mixed-method approach, where feedback of the results flows back into the evaluating process, can support synergies between product developers and UX designers. As a result, the findings can echo into more efficient and effective product development, providing automated data collection and driver behavior evaluation that saves company resources and significantly decreases the time for this type of assessment.

The proposed Driver Coach framework is a general approach to implementing user adaptation to any in-vehicle system or function. This design presumes the establishment of a new communication channel between the user and the smart software system to introduce, promote, and explain system functionality to drivers showing how users' behavior could be manipulated to increase the efficiency of driver interactions with in-vehicle systems.

The Driver Coach app for PA users was designed as a case study to verify the feasibility of the coaching process in a particular OEM, considering the existing constraints for data collection and technical limitations associated with the coaching process. The Driver Coach app for PA users is fully implemented to demonstrate in practice that it is possible to gather diverse data from actual driving, enforce real-time data analysis, and consider the driver's reaction to the PA Coach notifications. **Paper F** presents the first validation results on the effect of this type of support on drivers' behavior. In summary, this work contributes with a practical method for enhancing the design of in-vehicle systems in production cars and provides new verified knowledge of how users can be stimulated to use specific vehicle systems.

6

OUTLOOK

This chapter presents the results and the research challenges identified and reflects on future research possibilities.

6.1 CONCLUSIONS

The conducted research revealed the great potential of vehicle data utilization for data-driven user behavior evaluation. In the course of this research, a number of activities that contributed to the research was carried out: (i) the feasibility of vehicle data from the Volvo ND study was investigated; (ii) the required data for ADAS driver and system evaluation were specified; (iii) all measuring parameters relevant for the ADAS evaluation (i.e., driving context, measuring period, specific user parameters, etc.) were investigated and defined; (iv) collected data was statistically analyzed on different levels of abstraction, starting from average comparisons between drivers or groups of drivers and becoming more rooted to the one driver evaluation level or even one single driving activity evaluation level.

The vehicle data analysis revealed that the objective assessment of driver and system performance, as well as the driving context variables such as the weather, road and traffic conditions, is possible. Vehicle data offer the possibility to determine individual user behavior, and to describe, categorize, and compare this to the average within a group. Furthermore, they allow the identification of specific use errors or a change of driver's use strategy. Vehicle data analysis enables the understanding of the severity of detected issues by checking the number of vehicles or the amount of DCs that accounted for the same problem. All of the above mentioned factors make the applicability of vehicle data for driver behavior evaluation meaningful.

However, despite the significant potential of ND data for ADAS evaluation and the valuable results that can be achieved, there are still some limitations that need to be considered. One of the limitations is that although vehicle data allows context-aware driver and system performance evaluation, the underlying explanations for why objectively detected things happened cannot be determined through the vehicle data alone. Due to the restricted data collection procedures, it is often not possible to measure such human-related aspects as driver perception or driver subjective impression on the interaction with the system. Therefore, in the course of this research, an explanatory sequential mixed-method was designed and tested at Volvo, as an industrial case for ADAS driver behavior evaluation. The combination of quantitative and qualitative approaches contributed to more effective ADAS evaluation, where the driver behavior is considered together with human-related aspects. The practical implementation of the method showed the ability for a comprehensive view of all factors affecting the ADAS usage: the driver, the system (including other subsystems affecting the driver or system performance), and the driving context that has a high impact on driver and system behavior.

Another limitation is the feasibility of vehicle data, which often restricts the study design and prevents a more comprehensive evaluation of driver interactions with the targeted system. Nevertheless, the means and methods for driver behavior evaluation are continually improving, meaning that the existing restrictions may cease to apply in the near future.

Thus, as part of the next step, the data-driven driver behavior assessment was conceived in the design of a real-time personalized Driver Coach system that, based on individual driver behavior, provides this driver with recommendations on how to improve his interactions with the targeted system. The Driver Coach design was implemented as a fully functioning Driver Coach app for PA users and tested in the Volvo ND study for four months. According to the design, the Driver Coach app gathers diverse data from actual driving, enforces real-time data analysis related to driver behavior and context understanding, provides coaching support to drivers in real-time, and considers the driver's reaction to the provided support. Further, based on the detected driver behavior change, the Driver Coach app reassesses the implemented coaching strategy for the particular user. It offers optimized suggestions of how the specific driver could further improve their PA use strategy. Practical implementation of the Driver Coach app, presented in **Paper F**, proved:

- technical feasibility of coaching process organization in a real-time driving environment
- possibility to identify coaching events in real time
- possibility to monitor the driver's behavior change
- possibility to implement self-adjustment of the coaching logic.

A first validation study proved the ability to manipulate driver behavior by communicating the function's capability and limitations, and by suggesting different traffic contexts for PA usage. The proposed structure of messages, namely mistakes, warnings, and recommendations, and the expected driver reaction to these types of messages, are well understood by most participants. The study results show the overall increase in PA usage. However, not all the users improved, and not all users with improvements increased their PA usage to the same extent. Therefore, the author recommends PA Driver Coach app improvements related to the logic and test environment set-up and proposes another round of product improvement with the new round of tests on users.

6.2 FUTURE WORK

Besides the proposed steps for logic and test environment improvement, the framework could be further improved or enriched by combining different models that solve existing gaps identified in this framework. These models could be stand-alone algorithms related to, for example:

- driver identification in a shared vehicle
- driver state assessment
- driver distraction assessment
- driver workload understanding
- driver behavior prediction models
- other models that help to understand drivers better.

The better the logic is informed about the driver, the better it can understand the driver's needs and identify the best time for driver interaction. However, the added approaches need to be tested and verified in isolation before merging them with the existing design, which will require additional time and effort.

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