MIXED-METHOD DESIGN FOR USER BEHAVIOR EVALUATION OF AUTOMATED DRIVER ASSISTANCE SYSTEMS: AN AUTOMOTIVE INDUSTRY CASE

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ABSTRACT

Automotive systems are changing rapidly from purely mechanical to smart, programmable assistants. These systems react and respond to the driving environment and communicate with other subsystems for better driver support and safety. However, instead of supporting, the complexity of such systems can result in a stressful experience for the driver, adding to the workload. Hence, a poorly designed system, from a usability and user experience perspective, can lead to reduced usage or even ignorance of the provided functionalities, especially concerning Adaptive Driver Assistance Systems.

In this paper, the authors propose a combined design approach for user behavior evaluation of such systems. At the core of the design is a mixed methods approach, where objective data, which is automatically collected in vehicles, is augmented with subjective data, which is gathered through in-depth interviews with end-users. The aim of the proposed methodology design is to improve current practices on user behavior evaluation, achieve a deeper understanding of driver's behavior, and improve the validity and rigor of the named results.

Keywords: Human behaviour in design, Industrial design, Evaluation, Sensors data, Qualitative data

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1 INTRODUCTION

The well-recognized trend of in-vehicle connectivity drastically transforms automotive systems from purely mechanical to smart, programmable systems (Tornell *et al*., 2015). These systems react and respond to the driving environment, considering traffic, road and weather conditions. They communicate with other subsystems for driver support through higher convenience and safety.

The complexity of these systems and difficulty of tasks that an average driver has to perform can affect the driver's experience negatively, e.g. instead of adding support and comfort, it can result in a very stressful experience for the driver through an additional task. Hence, a poorly designed system, from an usability and user experience perspective, can lead to reduced usage or even ignorance of the provided functionalities, especially concerning advanced driver assistance systems (ADAS), where trust in the system performance is required for the adoption of the system (i.e., the braking, accelerating, and steering activities delegated to the vehicle system). A case that illustrates this is system-initiated deactivation of the driver assistance system without the understanding of the driver about why the system disengaged. The understanding of how the system works and clear communication between the car and the driver are key factors that should be prioritized during initial use studies and the development of a product. Following this, the investigation of driver behavior and user needs become a central aspect in the successful development of driver assistance systems.

Driving behavior has traditionally been viewed as a problem of guidance or control, or purely a human factors problem. These views arose together with the complexity of ADAS and the increasing demands on human abilities. While both views are relevant, none of the described are fully adequate, which is shown in the composition of driver behavior through two separate components; driving skills and driving style (Elander *et al*., 1993). Chen *et al*., (2013) further define driving skills as the attitude of a driver, while driving skills further describe an individual's driving habits. Michon (1985) argues that driving cannot be described simply as a combination of tasks, and introduces three levels of tasks that determine driving behavior, i.e., strategic (planning), tactical (manoeuvring) and operational (control). This shows that the development of Advanced Driver Assistance Systems has changed the nature of driving significantly - from a once controlling role, the driver is now co-operating with different automated functions offered by the car. This creates the need for the driver to attend to several goals at a time (Hollnagel *et al*., 2003).

Automated Driver Assistance Systems are semi-autonomous 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). In the case study presented, two functions of the ADAS in Volvo vehicles, namely Adaptive Cruise Control and Pilot Assist, were the focus of investigation. The Adaptive Cruise Control (ACC) function helps the driver to maintain the vehicle's speed with a preselected time interval to the vehicle positioned in front. ACC is usually enabled during long journeys with steady traffic conditions. It is achieved using vehicle cameras and radar and automatically adjusts the vehicle's speed with regard to other objects moving in front. This is defined as a Level 1 Driver Assistance by SAE (2018) standard J3016. The Pilot Assist (PA) function is an additional support, on top of the ACC function, which also helps the driver to keep the car in the lane. This is achieved using cameras and the vehicle's radar unit, but leaves the driver in full charge and with the responsibility to take back control of the system at any time. This is classified as a Level 2 Partial Automation System (SAE, 2018).

This high level of interaction between the user and the car requires a very good understanding from the user about how the system works and who has the responsibility for the driving activity at any particular moment. The user behavior in such systems cannot be described by linear logic, it instead becomes very context dependent, which makes it difficult to describe, use and evaluate. Often it is useless to ask users about their understanding because they simply might not be aware of the reasons for bad system performance. Users can be unaware of the fact that the prerequisites for the system activation were not fulfilled. However, if the driver sends the request at the moment when the system is not able to support him/her, the driver might decide that the system is not reliable and stop using it altogether. In such complex systems, where the authority for the driving activity swings from the user to the machine and back, it becomes highly important to understand how the system works and what limitations it has. This understanding is crucial for the ability to judge possibilities for system activation and continuous use.

Therefore, the involved resources of a company need to be effectively used for this purpose and aligned with the research and development processes. Both qualitative and quantitative approaches can support the user behavior evaluation processes. Commonly, the choice of a research approach is defined by traditions within the particular research field and depends on the quality of data resources, human expertise level and adopted methodology. In the automotive industry, the auto-generated objective data is usually poorly applied to the user experience evaluation process, since it is hard to capture the user's emotions and perceptions towards the system through technical data sets. Therefore, traditional assessment methods are used to facilitate in-depth interviews, observations or open-end questionnaires to obtain a holistic understanding of the user experience regarding a product.

Different types of user data utilized in these approaches contribute to different types of knowledge, benefiting the understanding of user behavior. Therefore, the combination of qualitative and quantitative methods can lead to better results than the use of each in isolation (Rovai *et al*., 2013). Both quantitative and qualitative methods of course have their strengths and weaknesses. The main drawback of a quantitative approach is the lack of explanation (Rahman, 2016). It is possible to detect events, but it is difficult to explain their nature and consider individual user perspectives. A subjective approach, on the other hand, focuses on the explanation of events, but it is difficult to generalize results and extrapolate to the larger population (Atieno, 2009). According to Bryman (2007), mixed methods research can not only be useful to assess findings in comparison to each other, but can create a complete report on the results that combines both qualitative data and quantitative findings through an in-depth discussion.

However, continuously increasing in-vehicle connectivity opens new capabilities for obtaining new objective usability data. Previously conducted studies based on objective data demonstrated that instead of simply collecting user performance data, we have the possibility to collect contextual information to support each and every event (Carta *et al*., 2011; Angelini *et al*., 2018). In the automotive environment, contextual information can include driving speed, event occurrance timestamps, GPS data, error frequencies, traffic, road and weather conditions. This user-related data is generated with high velocity and in real-time. The information gathered gives us the possibility to evaluate user behavior in different driving situations and indicates how well the user understands the system functionality. Objective data also offers the possibility to determine certain user behavior, as well as describe, categorize, and compare this to the average within a group. Further, it is possible to identify specific use errors, the usage of a particular function or the degrading of usage of a function over time. Furthermore, the data enables hypotheses to be set regarding user behavior patterns, based on purely objective data, which opens up new possibilities for quantitative research including data mining, network analysis, and predictive maintenance (Rovai *et al*., 2013). Additionally, the observed positive shift in the quality of the objective data allows us to design a comprehensive methodological approach that considers and incorporates quantitative research in combination with traditional qualitative approaches for user behavior evaluation. It can also be mentioned that qualitative approaches for user behavior evaluation are widely in use in the automotive industry today.

Consequently, we want to argue for a more holistic methodology design for user behavior evaluation in the automotive industry, to examine the impact of consolidation of quantitative and qualitative approaches in the development and substantial improvement of Advanced Driver Assistance Systems. The main objective of this paper is to propose a mixed methodology design for user behavior evaluation in the automotive industry. At the core of the study design is a mixed methods approach, including qualitative and quantitative methods, where the objective data, which is automatically collected, is augmented with subjective data gathered through in-depth interviews. The aim of the proposed methodology design is to achieve deeper understanding of user behavior, primary driver's perception on the use of driver assistance systems, and to improve the validity and rigor of the results. We have studied the case of ADAS evaluation, drawing on examples of different data-type utilization for the assessment of user behavior and needs in order to improve current practices on user behavior evaluation.

2 BACKGROUND

Qualitative research methods focus on the quality of things, trying to explain and describe, as well as discover the root causes of user behavior (Creswell, 2014; Meriam, 2009). Denzin and Lincoln (2005) describe this research approach as an attempt to understand things in their natural environment, by

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interpreting the phenomena based on the meaning that a particular user or a user group brings to them. Qualitative methods usually focus on gathering subjective impressions regarding the system usage, rather than targeting specific user tasks or identifying the variables that cause specific user behavior (Orlovska *et al*., 2018).

Qualitative approaches have a well-established methodology, based on usability evaluation methods (UEMs). According to the classification by Ivory and Hearst (2001), there are 132 documented UEMs that allow receiving user input at different stages of the product development process.

One of the main advantages of qualitative research is that it supports obtaining explanations about why different phenomena occur, what their nature is and how they can be described. Therefore, the human factor, i.e. user perception and needs, are the primary interest of qualitative studies. With the help of qualitative methods a deep and extensive evaluation of a product or system is possible. Participants are usually encouraged to freely express their opinions, which helps to build a discussion and elaborate on what they mean. Further, occurring events can be observed in their natural context, through different techniques, without reducing the complexity of the system, processes or tasks that are of interest. This enables the researchers to gain deeper insights and target problems at their root cause instead of only working on mitigating symptoms.

Although there are clear advantages to the use of qualitative research methods, there are often limitations, which need to be addressed. The most common issue underlying why qualitative methods are not applied is that qualitative studies are time-consuming. If stakeholders need to make an urgent decision then the qualitative study that takes months to administrate, conduct and analyse is not an option (Sallee and Flood, 2012).

Atieno (2009) pointed out that due to the relatively low amount of participants, qualitative methods have no statistical significance, which means that the findings from qualitative studies cannot be extrapolated to a larger population set with the same confidence level as quantitative results. Hence, the low amount of participants reduces the possibility to classify users or issues they experience into different categories. Further, he argues that 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 phenomena (Atieno, 2009).

Rovai *et al*. (2013) criticize qualitative research methods for their unreliability, and argue that different results may be achieved with different participants, or at a different time. Furthermore, they argue that a qualitative researcher cannot be seen as an independent individual, and point out that different research technics and the environment (e.g., the laboratory or questionnaire design) as well as the researcher's own perception can bias the participants' view, and affect the interpretation of the results if the researcher is not careful about their involvement and does not use a standardized approach which mitigates their influence.

Quantitative research often focuses on measurements that test hypotheses, determine an outcome and generalize conclusions (Denzin and Lincoln, 2008). The results 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, taken from extended user surveys or by using an automated method of data collection.

This approach and the technical solutions being facilitated make it possible to collect larger samples compared to qualitative research. Quantitative methods are especially useful when a systematic, standardized measurement is needed that makes it possible to generalize the conclusions from quantitative studies (Rovai *et al*., 2013). Rahman (2016) points out that quantitative approaches are independent from the researcher, and therefore the evaluation process is less biased by the interviewer's viewpoint, his/her appearance or questions. Further, he mentions that statistical methods, which are primarily used in quantitative research, are precise and rigorous, and therefore help to establish a certain level of trust towards quantitative methods among engineers.

It has to be mentioned however that the use of quantitative methods may give the wrong impression of homogeneity in a data-set. For example, the actual user experience of vehicle-owners and non-vehicle-owners may differ, and therefore measured in-vehicle user experience might not be applicable to the non-vehicle-owners to the same extent as for a vehicle-owner.

Another limitation of this type of data collection is that even though quantitative approaches allow the possibility to see what happened and how frequently the phenomena in question happened, the underlying explanations for why those happened cannot be determined through the data alone. Furthermore, due to restricted data collection procedures, it is often not possible to measure the full

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complexity of the human experience or a user's perception. Therefore, user experience is often divided into measurable areas and studied as a separate aspect (Rovai *et al*., 2013).

2.1 Current trends of user behavior assessment in the automotive industry

Despite the fact that both qualitative and quantitative research approaches are broadly applied in the automotive industry today, the majority of studies are conducted in isolation. Various evaluation groups of designers and engineers, with different backgrounds, conduct studies that are solely based on qualitative or quantitative data. This results in difficulties regarding knowledge transfer from one study to another and between different organisational groups.

The validity of the results for these studies is therefore questionable, and the need to combine different approaches has to be recognized. Moreover, the results of different approaches are mainly used for the comparison or validation of their findings, but rarely aim to improve the quality of the conducted study itself. This neglect could be explained by the seemingly low compatibility of qualitative and quantitative data, which often leads to the practice of prioritizing one of the approaches over another. To summarize, qualitative approaches, on the one hand, are mainly implemented in user-related studies, due to long-term traditions within automotive OEMs. On the other hand, quantitative research methods, are broadly used for the evaluation of a vehicle's mechanical parts, but are rarely used in user-related research.

However, a brisk development of data sensors and a variety of information generated by the automotive production platforms clearly indicate the need for a new approach that can consider both directions; the possibility of extended quantitative data utilization and qualitative insights.

Since both quantitative and qualitative approaches have their strengths and drawbacks in relation to user-related studies, an intelligent fusion of both approaches, implemented effectively, can improve the quality of user-related studies and increase the validity of the results.

While mixed method approaches are widely described in the literature, our understanding is similar to Johnson and Onwuegbuzie (2004), who define this as a type of research where qualitative and quantitative approaches are combined to achieve an in-depth understanding of the subject phenomenon and gain a validation of the results. Moreover, Green (2007) states that effectively designed mixed-method research can mitigate the inevitable method bias.

3 METHODOLOGY

The requirements for the data retrieval were set based on usability evaluation questions. The questions were previously designed by a usability evaluation team, and the focus was on spotting any trends in user or system behavior, or the possibility of finding any correlations in user behavior to reveal possible usability problems.

In the described case study the data was gathered with the help of Volvo Cars in-vehicle data collection system, named WICE, which enables the field evaluation of vehicles equipped with the device. In detail, the WICE system is a telematics platform providing data access from participating test vehicles, and consists of two major parts: (i) the in-vehicle telematics data measurement system and (ii) the back-end server infrastructure, together with a web-based front-end user interface that includes data storage units and database. Overall, the system provides metrology services, including various signal types for collection and measurement. The WICE system is able to manage information from the vehicle fleet by keeping track of map-based positioning, mileage, and uptime or diagnostic codes.

Data acquisition: the WICE equipment was installed in 127 vehicles, with the agreement of their owners to participate in the study. However, only 109 vehicles were able to deliver any data. The rest 18 vehicles were therefore excluded from the data analysis.

The vehicles represent three different geographical market segments; Europe (mainly Sweden, with drive cycles (DCs) within Europe), China and the United States.

Vehicles were divided into Internal (vehicle distributed among the OEM workers), and Service vehicles (public taxi and courier vehicles). The data collection was performed for a time period of nine months (from 01/07/2017 until 31/03/2018), and included all reported DCs, even the "empty" DCs (DCs when the ADAS support was not activated).

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Vehicle models and their configurations varied (five different models), but all vehicles had the same version of DSS on board. The number of vehicles was not constant during the evaluation period. If the vehicle was not demonstrating driving activity it was not included in the assessment.

The measurement parameters: every DC was recorded and evaluated, meaning that all activations and deactivations of the system made by drivers or the system itself were captured. Furthermore, a distinction was made between the user and system performance, to be able evaluate these separately, and examine how the driver performance affects the system performance and vice versa. The data representing the context of use was also included in the assessment, e.g. date of the event, vehicle speed, driving distance, time of day the activity happened, GPS data, weather conditions and others. Every single DC was documented with a unique file-name to be able to connect the vehicle to its data. The data analysis was performed with the help of Power BI - a software for statistical analysis. The preliminary results of the evaluation are presented in the following section.

4 PRELIMINARY RESULTS OF THE QUANTITATIVE STUDY

The quantitative study was solely based on data obtained from vehicle sensors. The analysis of this data revealed a number of possibilities for an objective user behavior evaluation, which will be listed below.

Finding 1: Objective data allowed us to measure the level of usage for ADAS functions. We were able to measure how ACC and PA were used by the drivers from 109 vehicles, with a high level of precision. Based on this, the average ACC/PA usage was calculated, and then compared to the individual driver's performance. Moreover, measuring and comparing the usage of ACC/PA functions in different geographic markets was possible and, in another step it was possible to evaluate and measure the usage of ACC/PA functions in different contexts, e.g. the usage in day/night driving hours, differences due to seasonal changes and good/bad weather conditions, different speeds drivers use for ADAS activation, the duration of usage time, and the usage of ACC/PA functions depending on DC length.

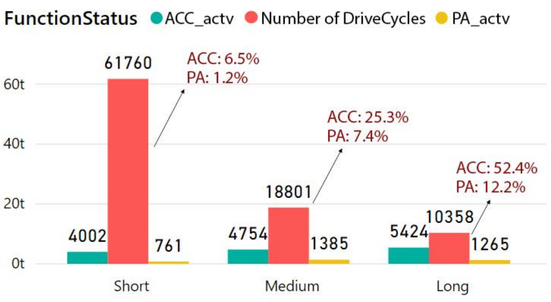

Figure 1. Average extent of ACC and PA usage for short, medium and long DCs.

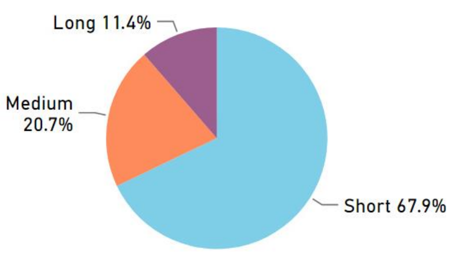

Figure 2. Average distribution of short, long and medium DCs.

Finding 2: Objective data allowed us to differentiate patterns/trends in user behavior by clustering drivers who behave similarly under the same conditions. A certain trend in user behavior was discovered concerning the longer DCs, where the data indicated that there was a higher probability that the driver would use DSS. To illustrate this we categorized all DCs into the following groups: short DCs: DC ≤ 15 km; medium DCs: 15 km < DC ≤ 50 km; long DCs: DC > 50 km. Figure 1 shows that the usage of PA in long DCs exceeded the usage in short DCs by a factor of 10 (12.2% for long and 1.2% for short DCs). We have obtained the same results for the ACC usage (52.4% for long and 6.5% for short DCs).

Another trend that was observed is related to the distribution of short, long and medium DCs in driving activities. It was found that the everyday driving activity consisted mostly of short DCs (67.9% of total driving activities, see Figure 2), and long DCs are performed occasionally (11.4% of total activities).

Finding 3: Objective data allowed evaluation of system performance. In this particular study the focus was on the system reliability

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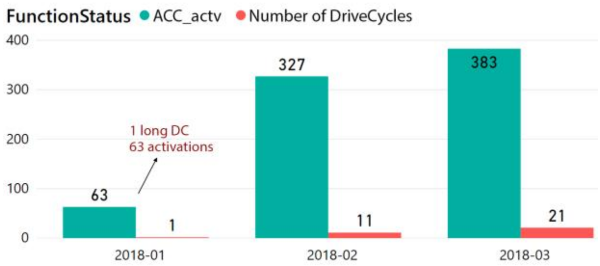

Figure 3. The number of ACC activations for one vehicle (long DCs) in the period from 01/01/2018 until 31/03/2018.

attribute. System reliability is the ability of the functions to perform under stated conditions for a specified period of time. According to the data obtained, the system reliability is stable and does not depend on seasonal changes, day/night driving hours or activation speed. No correlation was found. However, the data revealed that the number of activations during one single DC could be very high (see Figure 3).

Finding 4: System Reliability varies for different users, performing in the same driving conditions. To be able to evaluate the system reliability the number of requests for PA activation was compared to the number of PA activations that drivers sent and received from the ADAS. Some drivers received a positive response to their requests more often than the others, although the driving conditions for both user groups remained more or less the same.

Finding 5: We were able to detect specific usability issues and measure their magnitude. The use of sensor data allowed us to detect usability issues such as no usage of ADAS, a very low usage or decrease in time of the function usage. The magnitude of these issues was measured by looking into how many drivers anticipated the same problem and usability issues could be prioritized, pointing out which problems are more critical for different user groups, and what issues need to be addressed first.

The findings analysis described made it possible to formulate four hypotheses regarding driving behavior patterns.

Hypothesis 1: Based on the finding that ADAS usage depends on the DC's length, we assume that drivers have a different type of mindset for longer DCs. Adapted driving strategies could be applied to different driving situations. The data analysis shows that often drivers activate ADAS functions within the first 15 km, which they normally do not do if they drive only or less than 15 km. Most likely drivers know that driving long distances is more tiresome, due to long concentration on the driving task, from pressing the gas pedal or steering the vehicle and based on this previous user experience, they activate the ADAS in long DCs relatively early.

Hypothesis 2: The number of the system's deactivation and poor driver/system communication of deactivation causes could be the reason for low user satisfaction regarding the system performance and could lead to a decrease in usage. As shown in Figure 3, the number of system deactivations could be high for one single DC. However, it does not mean that it is a user who always has to send the request for system activation. In the majority of cases the system can recover from deactivation by itself. However, constantly switching between ON/OFF status could be perceived as poor system quality and result in distrust towards the ADAS functions.

Hypothesis 3: Drivers with low system usage struggle to comprehend the system complexity. We have come to this opinion due to the assumption that users who do not use ADAS functions, especially PA, as part of their everyday activities, have much less possibility to remember anticipated problems and bring the updated knowledge to the next session. Data shows that learnability for most users who do not use PA extensively is consistently low and has not improved during the nine months measured.

Hypothesis 4: System Reliability varies for different user groups performing in the same driving conditions and depends on the experience level within a group. It can be assumed that users with better system comprehension, who know how the system works, what prerequisites it needs and what limitations it has, can anticipate the right moment to interact with the system, and therefore get better support from the system.

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To be able to verify this hypotheses in the future, the authors propose a comprehensive study design for user behavior evaluation described in the next section.

5 HOLISTIC STUDY DESIGN PROPOSAL FOR THE EVALUATION OF ADAS

To work with mixed-methods research throughout the development process is a strong approach to reach breadth and depth of understanding, and therefore a holistic view of a problem. Following the basic ideas of a general systems theory, which is based on the philosophy of holism, one assumes that the whole is more than the sum of its parts, and therefore the whole defines the nature of the parts. This idea is based on the thought that the parts are dynamically interrelated, which means the interactions and connections of the parts need to be addressed to obtain a holistic understanding of a system or problem (Skyttner, 1996).

In conclusion, the holistic perspective on a system suggests that the parts of a system cannot individually do what the system as a whole can do. Regarding current research and development practices, and assuming that the driver and vehicle are our system, this would mean that a quantitative or a qualitative approach used independently will not lead to understanding how the system as a whole behaves, because the parts of it are in close interrelation, interacting and influencing each other. This means that in order to gain a holistic understanding of the interaction between driver and vehicle, and the factors that influence that relationship, one has to combine different approaches and regard all the variables the system consists of. Therefore, a mixed method study design for the evaluation of ADAS is a promising approach to pursue a comprehensive understanding of user needs and user behavior with regard to the usage of those systems. Future research should therefore apply an explanatory sequential design procedure (after Creswell & Clark, 2018), as shown in Figure 4.

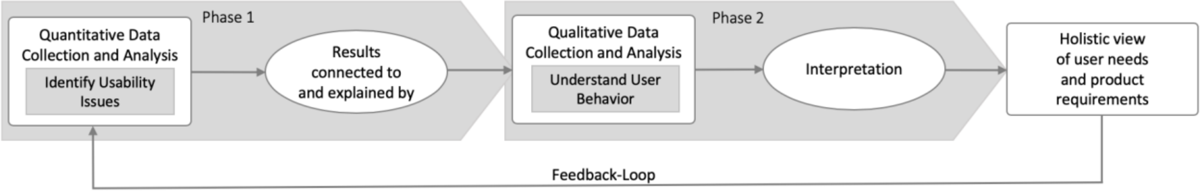

Figure 4. Explanatory sequential design

An explanatory sequential design occurs in two distinct phases. The design for this case study starts with the collection and analysis of quantitative data. In this step objectives are defined, evaluation questions are set, and the target groups are classified. The WICE equipment must be installed in the vehicles for data gathering. Short questionnaires are sent to all participants to receive insights regarding the planned vehicle usage, e.g. shared vehicle or sole driver, private use or work purposes. It is also important to know the level of expertise of the users with regard to the evaluated systems, therefore one has to regard if the driver is a first time user or experienced.

Based on the evaluation, the results need to be connected and relevant measuring parameters need to be defined. Behavioral data must be measured, including user and system performance, as well as contextual information such as the weather conditions, the road conditions based on GPS-data etcetera. The data analysis has to be performed with the focus on the defined objectives and questions formulated beforehand. In our case this addresses the level of usage, the detection of usability issues, and the identification of various trends and patterns in user behavior.

This first phase is then followed by the collection and analysis of qualitative data in order to explain or expand on the quantitative data set. The subsequent design of the qualitative phase has to be designed, so that it follows from the results of the quantitative phase, e.g. seek validation for the set hypotheses based on the analysis of the objective data, or try to explain emerging phenomena. The qualitative study design therefore needs to be focused on the clarification of the subjective reasoning of the drivers, inside the detected target groups, in order to understand the specific user behavior and needs, and be able to map out the interdependencies that influence the system usage. The authors intend to reach this goal by facilitating the use of semi-structured in-depth interviews with the drivers of the cars that the quantitative data was gathered from. Interviews are a common technique to gather in-depth feedback about end-user experiences with a system, since these allow the users to discuss and provide any desired input regarding the evaluated system within an open-ended questions format.

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In a final step, the authors plan to feedback the qualitative findings to the quantitative level for further verification. For a full understanding, it has to be assessed if a particular user explanation applies every time in the same context, and how other users behave under the same conditions. Further, it has to be investigated if the qualitative explanations can be generalized with the help of the quantitative data. This mixed-method feedback-loop can also help to identify other relevant data, not included in the previous analysis that can be used in the further quantitative assessment. If a specific interaction between user and system was detected during the qualitative data collection, the automotive company can draw conclusions about other possibilities to include new sensor data into the quantitative evaluation to be able to track a specific behavioral pattern detected during the qualitative study.

This parallel and sequential use of different methodologies, and the feedback of the results into the process, can support designers and engineers within research and development to create synergies in the development process, which will echo into a more efficient and effective product development.

6 DISCUSSION AND OUTLOOK

In this paper it is argued that a mixed-method research design based on objective and subjective data holds strong benefits for user behavior evaluation. Both quantitative and qualitative approaches complement each other, supporting assessment of different types, as well as validating results, and therefore creating more trust and understanding towards the data from industry professionals, who used to base their decisions only on precise numbers.

There are several disadvantages in the use of mixed methods, since the process can be associated with certain difficulties due to the flexibility in the methodical mix, which according to Cojocaru (2010) can be associated with methodological rigor fulfilment. Further, he states that epistemological contradictions can appear which could increase the gap and stimulate the competition between quantitative and qualitative methods (Cojocaru, S., 2010). This supports the argument that a mixed-method approach requires additional skills to enable a mixed-method utilization. Professionals with the set of skills for quantitative data evaluation are not usually equipped to conduct a qualitative study as well. This means that more specialists need to be involved in the evaluation process, and the collaboration between different departments has to increase in order to reach an efficient and effective symbiotic relationship between research and development.

However, the usage of an explanatory mixed-method approach in assessing user behavior in the automotive industry has advantages that cannot be achieved otherwise.

Firstly, the incorporation of quantitative methods into the evaluation allows different levels of abstraction to be set for the overall evaluation. Those levels can be classified into a general evaluation based on average comparisons, which allow an understanding of where in the interaction the issues emerge, and if the problem requires attention. In summary, abstraction levels help to save company resources, apply the effort to the problems that require critical attention, and are especially beneficial in the assessment of established products where an exploratory approach would take too much time. Further, how user behavior changes over time can be measured (e.g. learnability of a system) and how quickly users improve their skills and understanding of a system.

Secondly, the combination of these insights and identified gaps, with the “thick” data generated through qualitative approaches, delivers the key to understanding the preferences of users’ and their reasons for acting and using systems the way they do. Since the evaluated ADAS functions are complex, users can be unaware of system functionalities or be influenced by factors that the developers are not aware of. In particular, if the system is not providing detailed feedback to the user, this can result in behavior that was not anticipated and is hard to understand purely through quantitative data. Qualitative tools help translate this data into information that can be used to explain those gaps.

Furthermore, a mixed-method approach, incorporating a feedback-loop, allows developers and designers to map “real reality” of usage against the “perceived reality” that users express and specify, requirements not only targeting technical solutions, but solutions enriched with user experience insights, which will lead to improved products. Further research on this topic therefore aims to apply the proposed explanatory methodology design in the described setting and investigate the application into the development process of a research and development group within automotive OEMs.

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