Data-driven user evaluation of ADAS (DADEL)

System perspective

Public report

Project within: FFI Traffic Safe Automation
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1. Summary

Advanced Driver Assistance Systems (ADAS, SAE Level 1–2) have the potential to enhance traffic safety and efficiency, but their effectiveness depends on a deep understanding of how drivers interact with these systems in real-world conditions. Today, evaluations of ADAS usage are primarily conducted in controlled environments, which often lack environmental and contextual diversity, and focus on early-stage interactions rather than long-term usage patterns. Furthermore, due to confidentiality constraints, it is difficult to evaluate mature ADAS concepts with users before release. As a result, design decisions are frequently based on limited data, increasing the risk of developing systems that do not align with drivers' actual needs, leading to disengagement, misuse, or non-use, with negative consequences for safety, efficiency, and user experience.

Simultaneously, the rise of connected vehicles has created new opportunities to collect large-scale data on ADAS usage. However, most of this data remains technical in nature, focused on diagnostics and system performance, and is not structured to support user-centered evaluation. Key parameters related to human-machine interaction, driver state, and behavioural context are often missing, and systematic methods for extracting actionable insights from this data are underdeveloped.

To address this gap, this pre-study explored the prerequisites for integrating real-world data into the design and evaluation of ADAS. Through literature review, interviews, and workshops, it identified the types of insights needed by UX designers and human factors specialists, assessed the current availability of relevant data, and proposed initial concepts for data-driven methods and tools. The study concludes that there is strong potential for innovation in this area, and outlines directions for a full-scale project focused on developing AI-based tools and simulation models to support continuous, user-centered evaluation of ADAS in real-world commercial operations.

2. Sammanfattning på svenska

Avancerade förarstödssystem (ADAS, SAE Nivå 1–2) har potential att förbättra trafiksäkerhet och effektivitet, men deras effektivitet är beroende av en djup förståelse för hur förare interagerar med dessa system i verkliga trafikmiljöer. Idag genomförs utvärderingar av ADAS-användning främst i kontrollerade miljöer, saknar variation i miljömässiga och kontextuella faktorer och fokuserar på tidiga interaktioner snarare än långsiktig användning. Dessutom är det, på grund av sekretesskrav, svårt att utvärdera mogna ADAS-koncept tillsammans med användare före lansering. Resultatet blir att designbeslut ofta fattas baserat på begränsad data, vilket ökar risken för att systemen inte

överensstämmer med förarnas verkliga behov, något som kan leda till systemen inte används, att de används på felaktigt sätt eller att de frånkopplas. Detta i sig kan medföra negativa konsekvenser för säkerhet, effektivitet och användarupplevelse.

Samtidigt har ökningen av uppkopplade fordon skapat nya möjligheter att samla in storskalig data om ADAS-användning. Dock är större delen av denna data teknisk till sin natur, med fokus på diagnostik och systemprestanda, och den är inte strukturerad för att stödja användarcentrerad utvärdering. Centrala parametrar kopplade till människa-maskin-interaktion, förartillstånd och körbeteende saknas ofta, och systematiska metoder för att extrahera handlingsbara insikter från dessa data är underutvecklade.

För att hantera detta gap har denna förstudie undersökt förutsättningarna för att integrera data från verklig ADAS-användning i design- och utvärderingsprocesser. Genom litteraturstudier, intervjuer och workshops har förstudien identifierat vilka typer av insikter som efterfrågas av UX-designers och experter inom människa-maskin interaktion, kartlagt tillgången till relevant data, samt föreslagit inledande idéer för data-drivna metoder och verktyg. Studien drar slutsatsen att det finns en stark innovationspotential inom området, och pekar ut riktningen för ett fullskaligt projekt fokuserat på att utveckla AI-baserade verktyg och simuleringsmodeller för kontinuerlig, användarcentrerad utvärdering av ADAS.

3. Background

Many traffic accidents could potentially be prevented, or at least mitigated, through the use of Advanced Driver Assistance Systems (ADAS, SAE L1-2). However, recent studies show that ADAS available on the market are not performing well and that they are often confusing or disturbing to drivers, leading to improper use or disengagement (Adiutori, 2020; CarCompliants.com, 2020; Green Car Congress, 2021). A Scania investigation further highlights that truck drivers frequently disengage ADAS in complex traffic scenarios – situations in which these systems are inherently designed to provide support (Ryberg, 2023).

Optimizing ADAS performance requires an understanding of the complex interplay between the driver, ADAS, and vehicle in real world (Adiutori, 2020; CarCompliants.com, 2020; Green Car Congress, 2021). However, current ADAS design relies mainly on controlled small-scale studies, which may not capture the full range of factors influencing driver behavior and experience, leading to oversimplifications and usability issues described above (Ryberg, 2023; Power, 2022). In contrast, companies in digital domains (e.g., web development), have integrated methods utilizing data from the real-world usage to obtain insights into user behavior (Atterer, 2006). In line with this, automotive user experts and designers advocate for methods that allow quick and continuous assessment of how users interact with ADAS in the real world (Ebel, 2023; Orlovska et al., 2020; Novakazi et al., 2020).

While Field Operational Tests (FOTs) and Naturalistic Driving (ND) studies provide valuable data on real-world usage of ADAS (Orlovska et al., 2020; Bärgman, 2015; ConnectedAutomatedDriving, 2024), they are limited to instrumented vehicles. This limitation can be overcome by connectivity. Connected vehicles continually transmit data on diagnostics, location, driving behavior, and environmental conditions to external platforms (e.g., fleet management system) (Karmańska, 2021). This data differs from FOT and ND data in e.g., frequency and quality, and it is today unknown to what extent it can support user-centric ADAS design. However, recent advancements in data-driven methods make utilization of such data very promising and a natural next step in ADAS evaluation and design (Ebel, 2023).

This pre-study expands the use of data from connected vehicle fleets. It also investigates how to combine benefits from data-driven methods with traditional human factors and user experience evaluation in ADAS design, a novel approach in the automotive industry. Potentially, this would enhance ADAS designers' ability to make more informed user-centric decisions based on extensive real-world usage of ADAS.

4. Purpose, research questions and method

Utilizing real world vehicle data in user evaluations of ADAS requires a novel methodology including data-driven methods encompassing a wide range of techniques, such as machine learning, data mining, and predictive modelling (Ebel, 2023). It is anticipated that data-driven methods can be utilized to enable automotive safety and user experience experts to design and evaluate new ADAS based on the usage of existing ADAS in real-world vehicles. This, however, requires an understanding of *how* such methods can be applied to the existing data and design processes.

The purpose of this pre-study was to investigate how to integrate data from real-world usage of ADAS into the design of new ADAS. The pre-study also aimed at proposing the direction for a full-scale project. It is centred around the following research question: *How can data from connected vehicle fleets in real-world traffic be used to generate insights that support user-centered design and evaluation of ADAS for UX designers, human factors specialists, and ergonomists?*

This pre-study was organized in three work-packages (WP1-3), Figure 1. WP1 dealt with project management. WP2 investigated how data-driven methods based on data from the usage of current ADAS could be used in evaluating and designing new ADAS. Using Scania as a use case, we made an inventory of relevant data that are collected from vehicles today as well as data that might be possible to collect in a near future. We also surveyed relevant data-driven methods and tools. These findings were used in WP3, to conduct a gap analysis between the needs and possibilities. Subsequently, we established an initial understanding of how data-driven methods could be utilized in evaluations and design processes of ADAS. WP3 outlined the gap and a direction of a full-scale project. Our approach involved literature review, interviews and workshops with researchers and practitioners in industry.

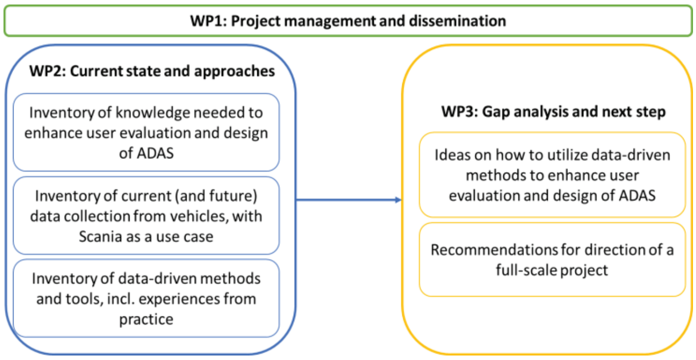

Figure 1 Pre-study set up with activities based on literature studies, interviews and workshops

5. Objective

The overall objective of this pre-study was to explore how data from existing vehicle fleets can be integrated into user evaluation processes of ADAS by means of data-driven methods. The goals of the pre-study were:

- Understand what type of user data is useful for designers of ADAS and what type of data is currently collected from real-world vehicle fleets.
- Understand how data-driven methods could be applied to the collected data and be integrated into evaluations and design processes of ADAS to achieve positive safety and efficiency aspects in traffic system.
- Provide a direction for a full-scale project that will focus on the creation, implementation and testing of a methodology to use large amount of vehicle data for evaluations and design processes of ADAS.

6. Results

Overall, the project goals were met. The following sections summarize the results related to each goal.

6.1 Literature review

This literature review aimed to explore how data-driven methods and real-world vehicle and driver data is used in the design and evaluation of ADAS and corresponding Human-Machine Interfaces (HMIs). The full review is provided in **Appendix A**.

The review shows that data-driven methods offer valuable insights into real-world ADAS usage, user behaviour, and system performance, complementing traditional, subjective user research. Data such as ADAS usage frequency, interactions, speed, road type, and gaze behaviour are used to identify user needs, usability issues, and patterns of acceptance or disengagement. There are also examples of how these data are combined with contextual information like weather or traffic conditions to better understand the use context.

Key advantages of using large-scale vehicle and driver data include real-world relevance, scalability, and the ability to link user behaviour to system performance over time. However, several challenges remain: lack of structured and standardized data, limited access due to proprietary systems, insufficient analytical tools, and privacy concerns. Notably, current methods often struggle to identify root causes behind behaviour, emphasizing the need to complement quantitative data with qualitative methods.

Furthermore, recent research suggests that machine learning and computational modelling can be used to predict driver behaviour and simulate user interaction, enabling early testing of ADAS and HMI designs. These methods support a dual approach: first identifying relevant behavioural parameters, then developing tools to visualize and interpret these insights in a designer-friendly format. The literature highlights strong potential for integrating big data into user research and design, provided appropriate methods and tools are developed

6.2 Knowledge needed for user evaluation of ADAS

To determine what information about ADAS usage is most valuable for improving user evaluation and the design of ADAS systems, we carried out a literature review along with interviews and workshops involving automotive experts at Scania, including UX designers, human factors specialists, and ergonomists.

Our investigation revealed that these professionals have diverse needs when it comes to understanding how drivers interact with and experience ADAS. Their requirements range from insights into how frequently specific functions are used, to understanding the relationships between system usage and driver behaviour:

- **Frequencies of usage**:
  - How often do drivers switch on/off FunctionX?
  - How often do drives adjust e.g., mirrors, seat, window?

  - Is button A more often used than button B?
  - How often do divers shift/change trailers?
- **Context of usage**:
  - When and where do drivers switch FunctionX on/off?
  - Unplanned stops (duration, frequency, location)?
- **Dependencies**:
  - What was the speed at the time of ADAS warning?
  - Why do drivers switch FunctionX on/off?
  - Did the driver brake because of other vehicles?
  - Under which environmental conditions do drivers open the roof hatch?
- **Driving behavior**:
  - General differences in speed/acceleration/deceleration
  - Differences depending on the type of road
  - How did the driver adjust his/her driving after the warning from FunctionX?
- **Driver state**:
  - How distracted are drivers when performing a task while driving?
  - What makes drivers tired?
  - Which display draws most attention when driving on highway?

Another key insight that emerged is the importance of longitudinal data. Experts emphasized the need for data that captures interactions and driver behaviour over extended periods of time, rather than isolated events. This is crucial for understanding how usage evolves, how trust in the system develops, and how long-term behavioural adaptations occur in response to ADAS features.

Consequently, accommodating these needs would require collecting and analysing a range of parameters, including the following:

- On/off status
- GPS location of activation/deactivation
- Activation/deactivation frequency
- Time of re-engagement after deactivation
- Warning signals (if present)
- Escalation levels of warnings
- Time taken to respond to warnings
- Driver reaction to warnings (e.g., lane return after LDW warning)
- Button press timing (e.g., before driving, after warning, during driving)
- Interaction method (voice control vs. physical button presses)
- Speed when the function is turned on/off
- Weather conditions when function is turned off/on
- Steering wheel sensor data (e.g., hands-off detection)
- Distraction detection parameters
- Button presses related to distractions (e.g., using infotainment or phone)
- Secondary task duration (start to end of a distraction-related task)

6.3 Current, and future, user data collection

Findings from our study support what has been previously highlighted in the literature: current approaches for evaluating driver interaction with ADAS in trucks face significant limitations. Specifically, evaluations are still largely dependent on experimental setups such as simulators or controlled test tracks. While these methods provide valuable insights, they are inherently constrained in several ways:

- Limited scalability: Setting up test environments and recruiting participants is time-consuming, resource-intensive, and limits the number of drivers and scenarios that can be evaluated.
- Subjectivity and reliability: Data gathered through interviews and questionnaires is often influenced by memory recall and subjective interpretation, potentially missing critical real-time interactions with ADAS features.
- Inability to replicate real-world complexity: Controlled tests struggle to capture the full spectrum of real-world driving conditions, such as varying weather, road types, and traffic situations that affect ADAS use.
- Confidentiality constraints: Competitive and legal restrictions often limit early-stage testing with real drivers, resulting in a lack of real-world user feedback before product release.

Although Field Operational Tests (FOTs) and Naturalistic Driving (ND) studies have contributed significantly to understanding real-world ADAS usage, they are typically limited to a small number of instrumented vehicles and are expensive to conduct. This restricts their scalability and the diversity of driving behaviour and environments captured.

A promising alternative lies in the use of connected vehicle data, which is automatically and continuously collected from vehicles that are used in real world transportation (Figure 2). This includes data for operational, maintenance, and technical purposes, transmitted to external platforms such as fleet management systems. Compared to FOT and ND studies, connected vehicle data offers broader coverage and greater scalability, though it often differs in granularity and frequency, and the type of parameters being collected. Put in another way, data from connected fleets are not primarily collected with driver-centric evaluation in mind**.** It often lacks granularity on driver-centric aspects like:

- Driver attention, distraction, or workload
- Motivation behind function use or avoidance
- Perceived usefulness, trust, or annoyance with ADAS features

Furthermore, data availability varies depending on vehicle model, hardware configuration, and the level of integration with backend fleet systems. Not all fleets capture detailed ADAS-specific data unless explicitly configured to do so.

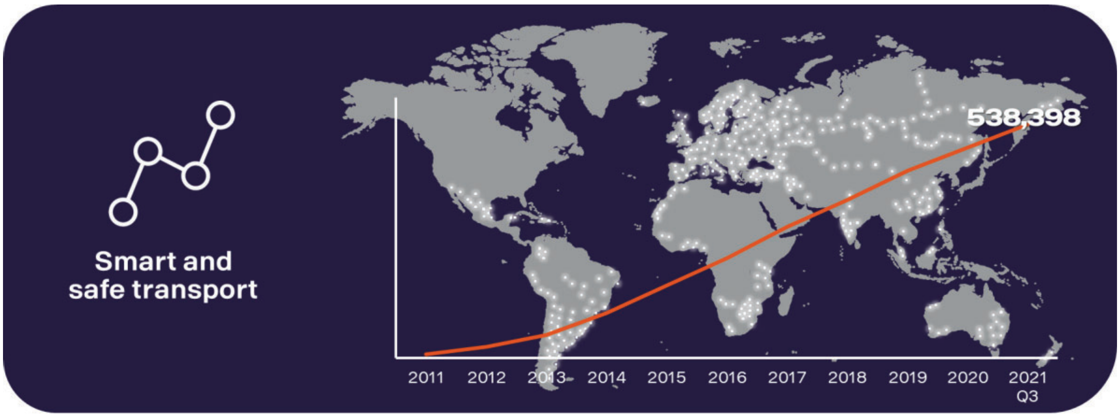

Figure 2 Scania's connected vehicle fleet exceeds 500k vehicles.

As of today, UX designers and human factors specialists make limited use of connected vehicle data. While at last some of the data that they need (see Section 6.1) is technically available, several challenges hinder its integration into user-centric design processes:

- It is often siloed within technical or engineering departments, making it difficult for design teams to access or interpret.
- The data is primarily technical, capturing *what* happened, but not *why*—i.e., it lacks insight into driver intent, cognitive load, or emotional response.
- Making meaningful use of this data requires advanced analytical capabilities and tools not always available within UX or human factors teams.

Nevertheless, recent advancements in data-driven methods, including behavioural modelling, pattern recognition, and machine learning, open up new opportunities for leveraging connected vehicle data to support user-focused ADAS design and evaluation. In parallel, the ongoing digitalization of vehicles is expanding the scope of data that can be collected, both in volume and variety. As trucks become increasingly software-defined and sensor-rich, new parameters are becoming available that are far more relevant to user-centric evaluations. These may include:

- Driver state indicators, such as drowsiness detection, gaze tracking, or attention monitoring (using in-cabin cameras or wearable integrations)
- Human-machine interaction data, such as touchscreen usage, button press logs, voice command patterns, or delays in responding to system prompts
- Context-aware data, including real-time weather, traffic density, and road quality
- Feedback and event tagging, allowing drivers to annotate or flag moments of confusion, discomfort, or disengagement with ADAS and similar in-vehicle features.

6.4 Inventory of relevant data-driven methods for user evaluations

Analytics – using LLMs
The interest in large language models (LLMs) have seen a significant increase in recent years. With large actors such as OpenAI, Google and Facebook investing heavily in the development and improvement of their own models. Starting with text processing more data formats have been added over time and can now also process images and tabular data among others, given that they fit the expectations, regarding format and size, of these models.

LLMs can be useful to structure and process data to present to a user. This both includes finding relevant information from databases, to interact with the user and to iteratively process the request and, finally present the outcomes. There is a large potential value in creating a user interface for databases that can suggest what data is needed to answer a specific request and find the appropriate code to extract the given information. The data would become accessible for those who do not have coding skills and enable them to work with the data.

One of the limitations of LLMs is their ability to hallucinate, i.e. they generate false statements (Huang et al., 2025). Therefore, when working with LLMs it is important to review and assess the outcome carefully. Another limitation stems from how the LLMs process data. They are designed to predict the next token based on the input tokens by finding the complex mapping of connections between them (Grzankowski, Downes & Forber, 2024). These provided input tokens represents the question, suggestion or task "asked" by the user, previous chat history, system messages, excerpts from databases and so on. LLMs are trained on tokens, and not directly on formats such as tables. While a table provides a structure where the relations between rows and columns can be seen at a glance by a human, LLMs need to have the information in the table encoded into tokens before processing the information and reduces it to a 1-dimensional format. To alleviate these issues there is a field of research dedicated to finding different ways of processing the data, including fine tuning and reasoning schemes (Lu et al., 2025).

User simulation
The field of user simulation focuses on developing artificial users and simulating their behaviour in specific systems (Balog & Zhai, 2025). By setting up an environment that provides a set of possible actions and one or more goals an artificial user interacts with the environment in order to reach the specified goal(s). There are currently examples of how this is done commercially (SmartBear, 2025). In the provided example software systems are used as the environment, which allows for clear digital responses to actions taken, a clearly defined action space and ease of calculating how well a goal has been reached.

6.5 Employing data-driven methods in user evaluation of ADAS

The pre-study identified two potential directions for a full-scale project (Figure 3). The first one should focus on data-driven methods to extract knowledge on driver behaviour and how drivers use and interact with existing ADAS functions and features. The purpose would be to understand what needs to be improved in the design of interactions, which in turn would enable new strategies, evidence-based argumentations, identification of unknowns and generation of new hypothesis. The second direction would be to develop a user simulation which, based on the extensive data that are collected from, e.g. the vehicles. This kind of simulation could support UX, human factors and ergonomics experts to develop and evaluate drivers' usage and interactions with new ADAS in frequent iterations to evaluate flaws and design concepts early in the design process.

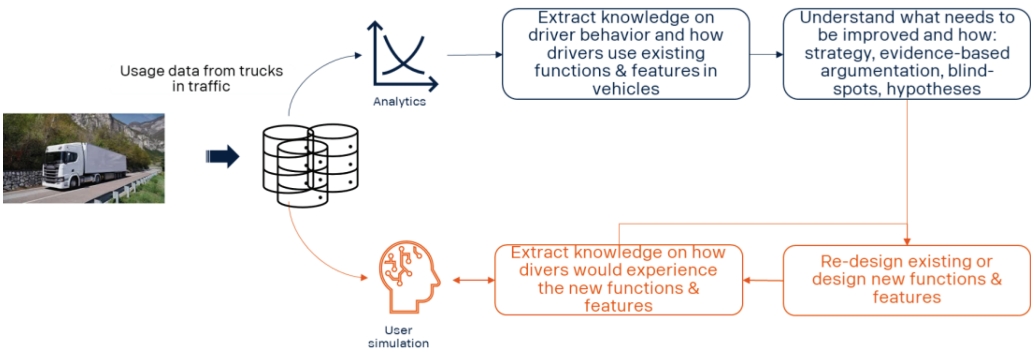

Figure 3 Potential directions for making use of data-driven methods in user evaluation of ADAS

As reviewed in section 6.4, there are multiple methods of extracting vehicle data, whether it is done with additional hardware or not. These methods have different impact on use of bandwidth, as well as different types of output format – and in most cases such variables may be difficult to alter.

The explorative nature of our envisioned project suggests that post-collection activities will be key for success such as filtering, re-formatting and analysing. Methods for actual data collection should ensure an ability to configure relevant data and its sampling/sending rate dynamically, to avoid lock in. Beneficial for answering specific questions (in the tool)

Data formats – formed by OEMs in many cases, which can lead to use of abbreviations and other non-understandable words. This could be handled on edge, or by the use of an additional database where we maintain meaning of different data item names, types, etc. This would be beneficial for employing any type of artificial intelligence in the analytics phase post-collection. Moreover, it is worth highlighting that user analysis for our purposes will benefit from additional data sources, e.g., weather, traffic and images, to establish richer context for why a certain behaviour is recorded.

As mentioned in 6.4 the data provided to a LLM needs to be encoded into a text format. Once a dataset is made available in a relational database several steps are needed to gather, process the data and convert it into the appropriate text format.

One potential method of creating an LLM approach to help users interact with a large database is to work with a table prompting agent. These approaches broadly contain three modules; memory, planning and action. The idea is to iteratively extract data, update the gathered information and process it until specific conditions are met, e.g. all the data types asked for are collected and formatted. The memory model like the name suggests can be used to store the information that is gathered from these iterative steps, planning decides on what actions to take based on current Information and the action realizes the plan (Lu et al., 2025). These actions can be prompting to the LLM, executing SQL requests to filter and retrieve data and embedding into a text format etc. It could also be to send retrieval-augmented generation requests to find excerpts from documents stored in a vector database to enrich the information.

This approach can be used to gather all the data necessary to perform a later analysis or based on the actions available to the agent perform it as a part of the reasoning model. If we consider an example where a user asks how the speed of the vehicle correlate with the turning on and off the ADAS we can envision the following broad steps for the agent. Send SQL queries to get speed and ADAS data iteratively until internal conditions for the request are fulfilled. Embed the tabular data into string format and structure user prompts, actions taken, extracted data, expected goals, etc.to reason what other steps need to be taken for the processing of the information and how it should be presented. Design or chose premade functions to send the gathered information to including graph creation, such as a correlation graph. Present the answer, figures and graphs to the user.

One of the large benefits of utilizing LLMs is their pretraining. That is, they have been trained on vast amounts of data by its creator. In some cases, this training is enough for the LLMs to be able to finish varying tasks without any additional input. On the other hand, this type of training is very general and not focused on the specific field or questions that they will be used for in the service of acting as a middleman between the dataset and the user. In these cases, finetuning can be an interesting choice. Finetuning means that a smaller amount of data is used to steer the LLM in the direction of the specific task. This could be done by training it on example inputs and show it what outputs it is expected to provide in those specific cases. By extension a finetuning approach could be set up to allow for user feedback to influence future finetuning and learn based on users' reactions to the output. A simple case of this is to allow users to mark if the answer was good or bad.

User simulations can be imagined as a future way of further utilizing the gathered data to create models that are capable of simulating how a user would interact with a system. An example case could be a GUI with buttons on it where the models action space is limited to the buttons it can press, and one goal is to reduce the number of actions needed to reach a specific screen given the graphical information. In this case there is a clearly defined and limited action space, goals that are easy to measure and the responses from taking an action clear. In a more difficult case of modelling the effects of different settings on the driver's seat on the driver the action space, responses and goals are not as clear and require additional steps of modelling.

A user simulation would not necessarily replace user studies as it is limited in its ability to represent how a real user would react to the system at hand. Instead, one of the main benefits of user simulations lies in their ability to quickly test new solutions or ideas with immediate feedback. One example for this is how the Smartbear service claims to simulate mouse clicks, where it would be possible to set up the program to be tested, add settings for the simulation and then get the result on how it would model a user using mouse clicks to interact with the program (Smartbear, 2025).

6.6 Directions for a full-scale project

Overall, our investigation highlights two persistent challenges in the current approach to ADAS evaluation and design:

- A lack of actionable insights into how drivers interact with ADAS in real-world conditions.
- A lack of systematic methods for extracting and applying these insights within user-centered design and evaluation processes.

More specifically, we found that the vast majority of data currently collected from connected truck fleets is technical in nature and focused primarily on diagnostics, vehicle performance, and operational metrics. While this data serves important engineering and maintenance purposes, it offers limited value to user researchers such as UX designers, human factors specialists, and ergonomists, whose work depends on understanding how drivers experience, respond to, and adapt to ADAS in their daily operations.

Key user-centric insights such as levels of trust in automation, reasons for function disengagement, driver attention and distraction, or reactions to system warnings, require parameters that are largely absent from today’s connected vehicle datasets. These include indicators of human-machine interaction (e.g., button presses, menu navigation, voice commands), driver state (e.g., fatigue, cognitive load, attention levels), situational context (e.g., weather, traffic, road types), and behavioural patterns.

Equally important is the lack of established methods and tools for making sense of this type of data – even when it is available. Most existing workflows in UX and human factors rely heavily on qualitative insights or small-scale controlled studies. These are time-consuming to conduct and difficult to scale, and they rarely incorporate high-volume, real-world data. Moreover, the data that is technically available is often siloed across systems, difficult to access or interpret without in-depth technical expertise, and not structured in a way that supports rapid analysis from a human-centered perspective.

To close this gap, there is a clear opportunity to explore how ADAS-related data can be made more structured, accessible, and usable – not only for engineering purposes, but also to inform user-centered design and evaluation. This requires not only enriching current datasets with additional user-relevant parameters, but also developing new methods for analysing and visualizing this information in ways that are meaningful to non-technical stakeholders.

By applying data-driven methods to (more complete and contextualized) connected vehicle data, researchers and designers could generate insights into driver behaviour, trust, engagement, and adaptation, insights that are difficult or impossible to obtain through traditional methods alone.

This pre-study therefore points toward several tasks of interest for a full-scale project:

- Investigate how data-driven methods can be meaningfully integrated into the daily workflows of user-centric professionals such as UX designers, human factors specialists, and ergonomists. This includes supporting faster, evidence-based decision-making and enabling identification of previously unknown challenges.
- Develop and evaluate an AI-based tool designed to support these professionals in analyzing ADAS-related driver behavior at scale. Such a tool should offer a user-friendly interface for querying, exploring, and visualizing relevant data, while maintaining traceability, ensuring that all insights are verifiable, explainable, and auditable, with clear links to the original data and analytical steps.
- Explore the use of user simulation modeling based on real-world data to create artificial user profiles and behavioral patterns. Such simulations could support early-stage testing and iterative design of new ADAS concepts, reducing reliance on resource-intensive field trials and enabling rapid prototyping of driver-technology interaction scenarios.

7. Dissemination and publications

The results of this pre-study have been disseminated within the participating organizations in the following way:

How are the project results planned to be used and disseminated?	Mark with X	Comment
Increase knowledge in the field	x	By exploring data-driven methods, which are new to the automotive industry when it comes user-centric evaluation of ADAS, the pre-study increases knowledge in the field and fosters innovation and strengthens Swedish stakeholders. With this project, Scania and its parent company TRATON have started building a foundation for their future user evaluation methodology. Being able to systematically extract relevant human factors knowledge from ADAS usage in real-world will enable: a) better knowledge about driver needs, b) more informed design decisions and development of more relevant solutions for larger population of drivers, and c) continuous updates to existing ADAS. For AiDEN, the pre-study provided insights into data collection on heavy vehicle side and helped advancing their data-driven solution. RISE has strengthen its multidisciplinary research involving data science, machine learning and human factors.
Be passed on to other advanced technological development projects	x	The results of this pre-study will serve as a basis for a full-scale research project in the field.
Be passed on to product development projects		
Introduced on the market		
Used in investigations / regulatory / licensing / political decisions		

As a next step in disseminating the results, a presentation and discussion are planned with the Road User Behavior group at SAFER. This group includes representatives from various stakeholder organizations, providing a strong platform for national outreach and engagement. To extend dissemination internationally, the findings will also be shared at the TRATON Knowledge Sharing Seminar. Additionally, the results, together with the related literature review, may be developed into a conference paper or a popular science article to reach broader academic and public audiences.

8. Conclusions and future research

This pre-study explored how data from real-world usage of ADAS (SAE Level 2) in commercial vehicles can be better utilized to support user-centric evaluation and design. While ADAS has the potential to enhance traffic safety and efficiency, current methods for evaluating driver interaction with these systems are limited. Both literature and our findings highlight that evaluations with drivers rely on controlled experiments with restricted participant diversity, short timeframes, and limited environmental variation, conditions that do not reflect the full complexity of real-world use.

At the same time, increasing connectivity of vehicles has resulted in the collection of vast amounts of data. However, our investigation reveals that most of the data currently collected from connected truck fleets is technical in nature, focused primarily on diagnostics, vehicle performance, and operational metrics. While valuable for engineering and maintenance purposes, this data does not sufficiently address the needs of UX designers, human factors specialists, and ergonomists who seek to understand user interaction, experience, and behavioural adaptation while using ADAS.

Key user-centric insights, such as trust in automation, reasons for function disengagement, driver attention and distraction, or how drivers interpret and respond to ADAS warnings, require parameters that are currently difficult to derive from most connected vehicle datasets. Missing from the current datasets are parameters related to human-machine interaction (e.g., button presses, menu navigation, voice commands), driver state (e.g., fatigue, attention levels), situational context (e.g., weather, road type, traffic density), and behavioural markers of acceptance to system use. In particular, serial, long-term monitoring of these parameters and connection to position data is lacking.

To close this gap, we conclude that additional parameters must be collected – parameters that better reflect real-world driver experience and support data-informed ADAS development. These additions would enable a richer, more holistic view of driver-ADAS interaction and allow for iterative improvements based on actual usage.

This pre-study also explored how data-driven methods, such as machine learning, behavioral modeling, and pattern recognition, can be leveraged to process and interpret these large datasets. It outlined a few promising future directions:

- Data-driven insight generation: Applying advanced analytics to connected vehicle data to uncover patterns in driver behavior and ADAS usage, providing designers with evidence-based insights to guide system improvements. This include development of a tool that allows UX and human factors professionals to retrieve, analyze, and visualize data in an accessible, explainable, and traceable manner as well as integration of such tools and methods into existing design and evaluation workflows.

- User simulation modeling: Using real-world data to create artificial user models that simulate driver behavior, supporting early-stage evaluation and testing of new ADAS concepts without requiring costly field trials.

In conclusion, while the connected vehicle ecosystem offers a strong foundation, unlocking its potential for user-centered ADAS development will require a deliberate shift: from engineering-focused data collection to a more holistic, human-centered approach that captures the *how*, *why*, and *when* of driver interaction. This shift is essential for bridging the current gap between system capabilities and user needs, and for ensuring that future ADAS are not only technically robust but also meaningfully aligned with the drivers who use them.

9. Participating parties and contact persons

The consortium consists of Scania (OEM, coordinator and problem owner), AiDEN Automotive (startup in vehicle connectivity and data management) and RISE (research institute with expertise in user centric design and data-driven methods). Given the complexity of the topic, the core project team incorporated a mix of disciplines ranging from data scientists to machine learning, human factors and safety experts.

SCANIA is a world-leading supplier of transport solutions present in around 100 countries. Scania is part of the TRATON GROUP together with MAN, Volkswagen Trucks and Navistar – which warrants global penetration of the results.

RISE is an independent, state research institute that offers expertise and around 100 test and demonstration environments. In this project, RISE utilized its multidisciplinary approach from previous projects (e.g., Enhanced ADAS, RE-ENGAGE, HARMONISE) to advance ADAS by combining expertise in human factors, data science and AI.

AiDEN Automotive is a startup with 12 employees, based in Sweden and USA. It provides software-only solution which streams real-time services across multiple vehicle brands, providing a simple and intuitive experience for vehicle owners, fleet owners, and drivers. With 100% GDPR and CCPA compliance, AiDEN's consent management feature ensures improved and personalized features.

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11. Appendix A: Literature review

This literature review used a tool that analyses the bibliography of scientific articles and maps related articles based on the similarity of the bibliography (https://connectedpapers.com). 14 related scientific articles including one PhD thesis and one licentiate thesis were found and 7 of these were ultimately included in the review, whilst most of it is based on the work of two authors. A broader literature review was not conducted due to a lack of relevant literature found in our search. The aim of the literature review was to answer four main questions and other related topics, which are detailed bellow.

What is the purpose of using data-driven methods and objective data from real driving according to previous research?

As vehicles become increasingly software-defined, there are large amounts of data such as location data and sensor data that provide insight into driving situations. Analyzing this data can be used for HMI evaluations, complementing research with subjective data (Orlovska, Wickman & Söderberg, 2018). Big data can be used to, for example, predict user behaviour, identify deviations in intended user behaviour, identify user needs, improve next-generation HMI (Orlovska, Wickman & Söderberg, 2018), identify user groups based on usage patterns (Ebel, Lingenfelder & Vogelsang, 2021; Ebel et al., 2021).

There is an opportunity to gain insight into real-world usage of ADAS with large amounts of data, and thus be able to evaluate user behaviour and ADAS performance to identify improvements (Orlovska, Wickman & Söderberg, 2018). Moreover, subjective measurement scales used in human-machine interaction research often focus on subjective impressions of the HMI but rarely take into account real-world performance in use or from the ADAS function (Orlovska, Wickman & Söderberg, 2018). Subjective measurement scales also have shortcomings in that the user may, for example, forget important information from the use, at the time of collecting the feedback (Orlovska, Wickman & Söderberg, 2018).

What types of vehicle and driver data can be used for what?

Some examples of vehicle and driver parameters are: ADAS usage amount/frequency distributed by driving scenarios, speed, road type, time of day. These parameters can be used to assess, for example, whether sensors need to be equally reliable in different light and weather conditions (Orlovska, Wickman & Söderberg, 2018). Another example is that HMI touchscreen interactions can be used to identify and optimize flows in tasks. (Ebel, Lingenfelder & Vogelsang, 2021; Ebel et al., 2023).

Moreover, another paper suggests: gaze behaviour, time on task, error rates, number of interactions needed to perform a task, correlation between in-vehicle information system (IVIS) interaction and driving data, can be used to identify the distraction of an IVIS (Ebel, Lingenfelder & Vogelsang, 2021).

Also, the frequency and duration of use of an HMI feature can be a valuable KPI for screening out or enhancing features. By detecting a low frequency and use duration of a HMI feature, vehicle manufacturers can come to the conclusion that the feature is undesired by drivers and from there it could be a decided to eliminate the feature. If on the other hand, a feature is used frequently and for substantial durations, it could be concluded that the feature is desired by drivers and thus the feature is kept (Ebel, Lingenfelder & Vogelsang, 2021; Ebel et al., 2023).

By combining data sources such as IVIS interaction and map data, it is also possible to gain insight into contextual information. As an example, IVIS interactions are reported to be different depending on the context. Contextual information can include, for example, the driving situation, how many passengers are in the vehicle, whether a mobile phone is connected to the IVIS. Also, the input modality is relevant for UX designers to get data on, i.e. whether drivers use voice, buttons on steering wheel, touchscreen to interact with IVIS (Ebel et al., 2023; Ebel et al., 2021).

In addition to the metrics that are defined in advance and extracted, large amounts of vehicle and driver data has an emergent property, in that it is possible to discover valuable information after extracting the data. This can be done by for example conducting linear mixed models analysis which helps researchers detect random effects from various variables. For example, if a hypothesis is being tested to investigate the effects of IVIS interaction on driving speed, it could potentially be shown that other factors such as light conditions, driving situation, modality of IVIS interaction or other factors are contributing to driving speed. The knowledge about which metrics can be used for HMI development can therefore expand as the research develops (Orlovska, Wickman & Söderberg, 2018).

What are the advantages and disadvantages of large amounts of vehicle and driver data and data driven methods?

Advantages:

- Human and system behavior view: Good for understanding user behaviour in combination with system performance, i.e. how user behaviour changes depending on system performance over time (Orlovska, Wickman & Söderberg, 2018).

- Real world data: Good for obtaining data from real-world driving environment compared to non-reality-like lab environments (Orlovska, Wickman & Söderberg, 2018), and real-world driving data is a valuable commodity for user research.
- Cheap scalability: The quantity and breadth of the sample does not make the evaluations more expensive once data availability and data extraction is set up, which is usually the case when conducting other types of data collections (e.g. lab setting experiments) (Orlovska, Wickman & Söderberg, 2018). The reason for the cheap scalability is that the data comes from an abundant vehicle owner pool.
- Symptom vs cause: large amounts of vehicle and driver data is effective in identifying problems with HMI because it provides a sequence of events, but it is not as good at identifying the root cause of the problems, i.e. why the situation occurred, and therefore it can be useful to see data-driven methods as a complement to subjective methods (Orlovska, Wickman & Söderberg, 2018).

Disadvantages:

- Lack of data structure: There is a lot of data but a lack of structure in the data that OEMs collect (Orlovska, Wickman & Söderberg, 2018). Vehicle data from CAN and FLEX RAY can provide insight into system performance, but interaction data may currently be in short supply, and this becomes even more challenging as interaction data can be distributed in a complex way in several different subsystems (Ebel et al., 2021).
- Unavailable data: Vehicle components are sometimes produced by many different manufacturers and access to these manufacturers can be challenging, making it difficult to build a picture of all available data (due to e.g. data protection and IP), but also difficult to make improvements (Ebel et al., 2021).
- Lack of analysis tools: There is a lack of tools to visualize and analyze this type of data (Ebel et al., 2023).
- User continuity: It is difficult to identify whether it is the same user driving the car or different users (Orlovska, Wickman & Söderberg, 2018). This is however different for heavy vehicles since each driver is often times logged.
- User privac**y:** Extra consideration is needed for user privacy, and classifying what data is sensitive and non-sensitive, together with going through legal authorization processes, increases the time needed for data-driven approaches (Orlovska, Wickman & Söderberg, 2018; Ebel et al., 2021).

How can large amounts of vehicle and driver data be used in the design process of ADAS and HMI?

Large amounts of vehicle and driver data can be used by for example simulating user behaviour with machine learning algorithms. This method also supports evaluations of early prototypes, instead of using in-house expert evaluations (Ebel et al., 2023).

By triangulating the quantitative data and supplementing with qualitative data, Orlovska (2020) presents an example where their data showed that the Pilot Assist feature in Volvo Cars vehicles was used less than the adaptive cruise control, and the only difference between the two features is that Pilot Assist adds lane keeping support in addition to adaptive cruise control, so the researchers were able to infer that there is something about the lane keeping support that makes users avoid the Pilot Assist feature. Two assumptions were then investigated using qualitative methods, namely that users either did not trust the lane keeping support to allow it to support the user, or the quality of the lane keeping assistance is too low for users to want to use it (Orlovska, 2020).

Related Topics

There is also research using large amounts of data from vehicles and drivers to use computational models to identify new ways of gaining insight into, for example, driver state or other driver behaviour. Researchers have previously used methods such as Adaptive Control of Thought-Rational (ACT-R) where the model can predict driver behaviour using an understanding of human cognitive functions such as perception and memory. The use of machine learning has also been used to predict human behaviour in interaction with technological systems (Lorenz et al., 2024). Lorenz and colleagues (2024) point out that there is a need for computational models predicting human behaviour that have a link to user interface design. For example, Kanaan and colleagues (2019) use machine learning on location data, speed, steering wheel angle, and other parameters to predict driver distraction. These approaches can be described as a post-processing of big data where the initial data from vehicles are used to identify other data types with the help of computational models.

Conclusion

There is a variety of data that can be captured from vehicles that can help design researchers to predict driver behaviour and then use the information for the development of services and user interfaces. Some parameters are clearly linked to driver behaviour such as driver distraction, while other parameters such as use of certain IVIS features can be investigated using computational models and machine learning to determine if they can predict driver behaviour and in turn have a role in design research. The use of large amounts of data and data-driven methods can thus have two important steps towards use within user research, where the identification of important parameters is one step, and where the development of a useful data visualization tool that design researchers can use is another step.