

BIG FUN

Public report

Project within Elektronik, mjukvara och kommunikation - FFI

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Fordonstrategisk
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FFI in short

FFI, Strategic Vehicle Research and Innovation, is a joint program between the state and the automotive industry running since 2009. FFI promotes and finances research and innovation to sustainable road transport.

For more information: www.ffisweden.se

1. Summary

The *BIG FUN* project (*Big Data-Powered End User Function Development For Commercial Vehicles*) is a collaboration between Halmstad University and Volvo Trucks. BIG FUN aimed to harness machine learning (ML) technologies to improve the design of commercial truck interactive systems. By leveraging novel datasets, the project sought to establish a holistic understanding of truck usage context to support human design work with ML-powered, data-driven insights.

A key focus was the development and use of ML algorithms to identify significant moments in truck journeys, further specified as the identification of overtaking maneuvers. These ML-driven insights were paired with user experience (UX) research to translate data patterns into actionable knowledge for system designers. This dual approach—combining ML advancements with UX principles—supported human experts in analyzing, contextualizing, and explaining identified moments of interest, fostering improved truck design processes and commercial mobility solutions.

The *BIG FUN* project followed two complementary tracks: one dedicated to ML development and the other to UX design. The ML track focused on data preparation and algorithm training, enabling the intelligent tagging of overtake moments in vehicle journeys. In parallel, the UX track gathered user requirements, designed interfaces for collaboration with ML systems, and validated insights through qualitative analysis. Together, these tracks delivered tools and frameworks for augmenting data-driven design in the commercial vehicle industry.

The outcomes of the project include enhanced methods for understanding truck usage, the design of a demonstrator interface for stakeholders, and actionable recommendations for integrating ML into design workflows. These advancements contribute to more efficient, sustainable, and user-centered commercial vehicle ecosystems, reinforcing Sweden's position as a leader in mobility innovation.

1.1. Sammanfattning på svenska

BIG FUN-projektet, ett samarbete mellan Högskolan i Halmstad och Volvo Trucks, använde maskininläring (ML) för att förbättra designen av interaktiva system för kommersiella lastbilar. Genom att analysera nya dataset identifierade projektet viktiga moment, som omkörningsmanövrer, och översatte dessa insikter till användbar kunskap via forskning inom användarupplevelser (UX). Projektet delades in i två spår: ML-utveckling, där algoritmer tränades för att markera händelser av intresse, och UX-design, där användarkrav samlades in och gränssnitt utformades för samarbete med ML-system. Tillsammans levererade dessa spår verktyg och rekommendationer som stärker datadriven design inom kommersiell mobilitet. Resultaten bidrar till effektivare, mer hållbara och användarcentrerade lösningar för kommersiella fordon och stärker Sveriges position inom mobilitetsinnovation.

2. Background

The mobility sector is undergoing a significant transformation, driven by the pressing need to address critical sustainability, health, and equality challenges of the 21st century. This shift is moving us away from traditional product-focused solutions and towards service-oriented approaches powered by data. The urgency to reduce carbon emissions, and evolving user demands requires finding flexible and innovative solutions. In this dynamic environment, harnessing the power of data is essential for navigating complexity and creating truly sustainable, equitable, and efficient mobility services.

Volvo Trucks, with its connected commercial vehicles, generates a wealth of data that holds immense potential for enhancing product and service development. However, realizing this potential requires overcoming key challenges. Firstly, there is no established infrastructure and ways of working with data of this scale. Furthermore, extracting meaningful insights from this raw data and translating it into actionable design improvements is a complex task. The sheer volume of data makes manual analysis impractical, and we need to find ways to effectively integrate quantitative data (what and how much) with qualitative data (why) to understand the context behind key events around truck use and identify areas for improvement.

By bridging the gap between data-driven insights and qualitative research, we can unlock significant opportunities to optimize product development. This approach can lead to more efficient, usable, safe, and sustainable commercial vehicles. Data can provide a constant feedback loop for Volvo Trucks, producing real-world insights and highlighting areas for improvement. These advancements will not only bolster the competitiveness of Swedish commercial vehicles on a global scale but also foster collaboration across industries and empower stakeholders like drivers and logistics workers.

The increasing digitalization of trucks has resulted in a wealth of data on truck journeys. This rich dataset contains insights that pinpoint specific areas for truck improvement. However, the human element remains crucial, as humans have the expertise, experience and human sensibility necessary to develop trucks in a successful way, as evidenced by Volvo's history. Effective user experience (UX) design ensures that data-driven insights are both relevant to real opportunities for improving truck design and integrated into existing workflows that empower human truck developer teams. This project has produced direct benefits for Volvo Trucks and valuable knowledge for the entire Swedish automotive industry, paving the way for the integration of bespoke machine learning insights into design and development processes.

3. Purpose, research questions and method

BIG FUN contains two parallel strands of work that collaboratively address the research questions of BIG FUN. The first strand is UX research, and the second strand is Machine Learning research.

3.1. UX Research methods

The UX studies in BIG FUN investigated the integration of machine learning (ML) into truck Human-Machine Interface (HMI) design, focusing on current data practices and the potential role of ML in enhancing design workflows. Conducted within Volvo Trucks, the research combined *qualitative methods, case studies, and thematic analysis* to explore how designers currently use data and envision ML tools addressing challenges in decision-making. *Semi-structured interviews* were held with industry professionals, including product designers, engineers, UX specialists, and strategy managers. Participants detailed their roles, experiences, and data usage practices, while also sharing insights on the future of ML in design. Using a design process canvas, the interviews prompted participants to walk through their workflows, discussing specific examples of truck functionalities to ground the findings in real-world practices. The basis for the discussions to investigate potential outcomes of applying ML was the widely spread double diamond design process (“The Double Diamond” n.d.) according to Figure 1.

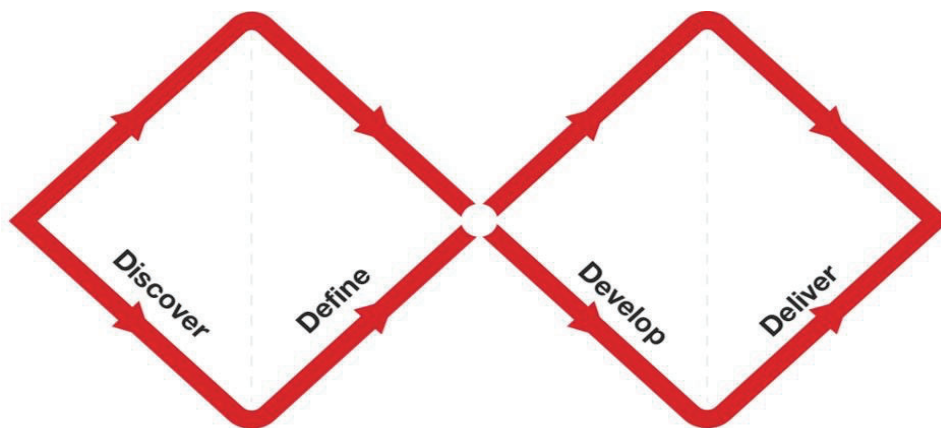


Figure 1: The Double diamond design process (*The Double Diamond*)

The interview transcripts underwent thematic analysis, beginning with open coding to tag *relevant insights, followed by axial and selective coding to identify broader patterns*. This process, supported by qualitative analysis software, revealed themes such as the decentralized nature of data practices, the reliance on human expertise for decision-making, and the need for ML to provide transparent, actionable insights.

Insights from the qualitative work and the ML work in BIG FUN were used in *co-design prototyping sessions* to develop prototypes of an ML-powered platform designed to provide human experts with relevant, understandable insights originating from truck trip data. The

prototypes were developed by the research team and professionals from Volvo Trucks using a co-design method where all stakeholders actively contributed to the design of a demonstrator prototype that exemplifies knowledge on how to design for ML-powered insights that fit into how professionals work within Volvo Trucks. This knowledge is likely also applicable for other commercial mobility companies given that the knowledge is adapted to each company's context.

Finally, the prototype demonstrator was used in design evaluation interviews with Volvo Trucks professionals, resulting in knowledge on addressing key machine learning issues such as transparency, explainability, trustworthiness, affordance for collaborative practices.

3.2. Machine Learning methods

The ML methods in BIG FUN investigated the applicability of several ML techniques to the detection of overtake maneuvers, identified during the project as one critical situation in truck driving. To achieve this aim, the research was divided into subsequent tasks comprising data acquisition, training of ML methods, and performance evaluation. The three main stages of an overtake scenario are illustrated in Figure 2 below.

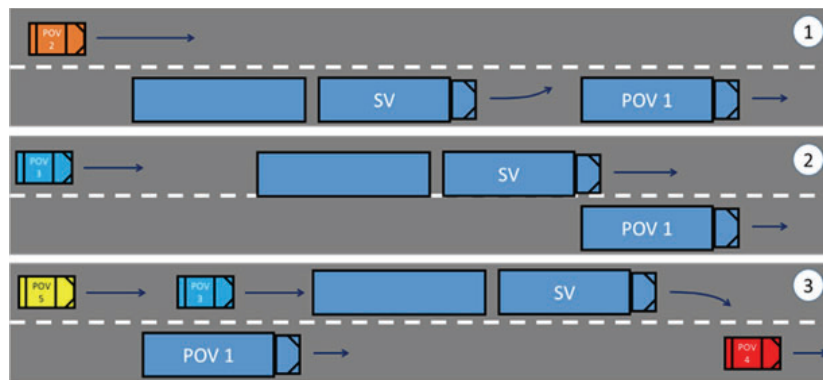


Figure 2: Use case sequence in overtakes
(SV = Subject Vehicle, POV = Principal Other Vehicle)

A database consisting of data from five real operating trucks was built during the project. These trucks are shown in figure 3. The trucks were equipped with loggers that captured CAN data from the trucks containing data such as pedals position, speed, acceleration, information of vehicles ahead (such as distance and speed), status of different involved signals like turning indicators, etc. A first set of labelled data represents a larger number of potential overtakes automatically recorded using a set of basic rules identifying CAN data likely to represent an overtake (e.g. the left turn indicator is activated when there is a vehicle a short distance ahead). The data set was recorded and verified by staff at Volvo from watching associated videos captured simultaneously by dedicated cameras in the trucks. This resulted in an equal number of data files of true overtakes (positive class) and no-overtakes (negative class), necessary to train ML methods. A second set of data contains CAN files recorded continuously across different driving sessions of the trucks, therefore they are unlabeled.



Figure 3: Examples of logged test trucks

Captured data from the project was then used to train classifiers and evaluate ML methods. Following a *literature study*, we identified the *classifiers commonly used* in classification tasks using CAN data and more importantly, we analyzed the *impact and value of different parameters* affecting data preprocessing, preparation and training of ML methods. Using the manually labeled data, we developed and trained a combination of two classical classifiers that provide over 90% accuracy in detecting the positive and negative classes on our captured data.

Another set of experiments has been set up and run to secure results before access to Volvo data is finished when the project ends, although the complete analysis of results will happen after the end of this project when *corresponding scientific publications* are written. On the one hand, *pseudo-labelling* techniques have been applied to process the data recorded continuously, which is unlabeled. Using the previously developed classifiers with labelled data, we have classified segments of the continuous data to obtain a set of candidate files of the positive and negative classes. This pseudo-labelled data has been used to evaluate a *classifier based on deep-learning methods*. Such methods are well-known to be data-hungry, and the small size of the labeled data turned out to be insufficient for appropriate training. Through appropriate training and the mentioned pseudo-labelling, we expect to increase classification accuracy of each class by a further 3-4 % up to 94%.

4. Objectives

The BIG FUN project focused on applying advanced quantitative analysis methods to identify key moments of interest in real-world vehicle journeys. These insights were combined with advanced qualitative analysis to uncover actionable opportunities, such as improving truck functionalities, features, and services to better meet the needs of commercial mobility. The project has the following objectives:

1. **Identified Significant Journey Moments:** Developed algorithms informed by expert domain knowledge and previous research to pinpoint overtakes, which have been identified by mobility experts at Volvo Trucks as moments of significance in truck journeys. CAN bus data was used in the identification of these moments, with video

- footage used to verify actual overtakes among the potential overtakes. While more extensive use of video footage was a potential additional data point, the project focused on CAN data since there was already a lot of untapped opportunity in this data set given the lack of previous research in the specific identified use-case.
2. **AI-Enhanced UX Design work:** Explored how to design a service that allows human experts to leverage AI/ML-identified insights to support qualitative research and generate actionable design insights to guide decision-making for commercial mobility.
 3. **Created a Demonstrator Prototype:** Designed a prototype of a tool for commercial mobility stakeholders, enabling them to make data-driven design decisions based on ML-generated insights from real truck CAN data.
 4. **Evaluated with Stakeholders:** Tested and refined the demonstrator interface with input from domain experts and relevant industry stakeholders.

5. Results and deliverables

This section outlines the key outcomes and deliverables from the BIG FUN project, which integrated machine learning (ML) and user experience (UX) research to enhance the design and functionality of commercial truck systems. The results are categorized into work packages, each addressing specific goals such as algorithm development, interface design, and stakeholder engagement. These deliverables demonstrate the project's progress in bridging data-driven insights with practical applications, contributing to more sustainable, user-centered, and efficient commercial mobility solutions.

5.1.WP0: Methodology

The UX design methodology for the BIG FUN project focused on building a deep understanding of the requirements and practices that will impact the integration of machine learning (ML) powered data analytics into the workflows of commercial truck development teams. Through a combination of qualitative research, co-design, and iterative prototyping, the methodology delivered insights and tools that advanced knowledge in designing for human-AI collaboration within the mobility sector. See the sequence of this approach illustrated in Figure 4.



Figure 4: Stages of the design research process

The project began with a focus on understanding the **technology and design requirements (D 0.1)** for ML-powered data analytics platforms. Observations and semi-structured interviews with professionals at Volvo Trucks, including UX designers, engineers, and strategists, revealed the

complexity of existing workflows and the challenges of decentralized data usage. Drawing from thematic analysis of the interviews, the study identified critical needs such as the importance of actionable, scenario-specific insights and the requirement for transparency in how ML systems generate outputs. These findings were supported by insights from the literature, which emphasized the necessity of explainable AI tools that align with user tasks and enhance decision-making without overwhelming the users.

To explore **domain-specific design requirements for ML-powered data analytics (D 0.3)**, the project engaged industry and academic stakeholders in co-design workshops to conceptualize tools that would effectively integrate ML insights into commercial mobility workflows. These workshops highlighted the role of human expertise in interpreting data and the importance of calibrating trust in ML systems through transparent interaction and adaptable outputs. The use-case identified as the most interesting concerned the identification of overtake maneuvers. To do so, a data collection campaign was then organized at Volvo to **secure data which was subsequently used for training and testing the ML methods (D 0.2)**. Prototypes were iteratively developed and refined to address these requirements, offering features such as user-defined clustering of data, interactive filtering options, and the ability to explore key moments of interest identified by ML systems, see illustrations of these in Figure 5.

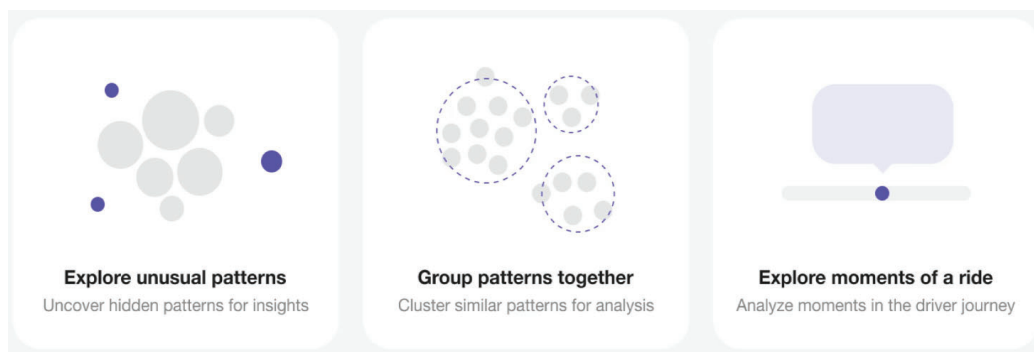


Figure 5: Explored function usage and driver behavior with AI

The iterative prototyping and evaluation process contributed to **knowledge from the prototyping and evaluation of the BIG FUN Demonstrator (D 0.4)**. Early low-fidelity prototypes tested functionality and usability, while high-fidelity iterations incorporated detailed user feedback to ensure alignment with real-world practices. Evaluative sessions with Volvo Trucks professionals validated the demonstrator's effectiveness in bridging the gap between raw data and actionable insights. Special attention was paid to the explainability of the tool, with features such as tailored explanations for users with varying technical expertise, ensuring accessibility without sacrificing depth in explanations.

The findings also informed **domain-specific knowledge for commercial mobility (D 0.3)** by providing actionable principles for integrating ML-powered tools into the workflows of mobility professionals. These principles centered around lifting the importance of designing for collaborative affordances, enabling users to explore, validate, and contextualize ML-generated insights effectively, balancing human agency, automation, and explainability. Prototyping insights underscored the need for intuitive interfaces that support iterative design processes and enhance user trust in the underlying ML technologies.

This work makes significant contributions to the Electronics, Software and Communication (Elektronik, Mjukvara och Kommunikation, EMK) objectives by addressing challenges in intelligent and reliable systems, aligning with the overarching goals of enhancing safety, sustainability, and connectivity in mobility. The development of explainable AI tools ensures transparency in how ML-powered insights are generated, calibrating user trust and enabling better decision-making. This directly supports safer mobility systems by reducing errors and enhancing operational reliability. The iterative prototyping process, emphasizing user-defined data clustering and interactive filtering, equips mobility professionals with actionable insights to optimize vehicle functionality and efficiency, contributing to greener outcomes through improved resource utilization and reduced environmental impact. Furthermore, by collecting knowledge and prototyping towards enabling seamless integration of ML-powered analytics into commercial truck workflows, the project advances connected goals by building knowledge that can enable future work on fostering data-driven collaboration between vehicles, users, and infrastructure. These innovations collectively strengthen the foundation for achieving "Gröna, Säkra och Uppkopplade" (Green, Safe, and Connected) mobility within the commercial vehicle sector.

5.2.WP1: Requirements for Machine Learning-powered analytics

Insights from Volvo Trucks domain experts and relevant literature highlight the intricate challenges and opportunities in integrating Machine Learning (ML) into truck Human-Machine Interface (HMI) design. Domain experts emphasize the decentralized nature of data practices and the critical role of human expertise in decision-making. This aligns with findings from the literature that underscore the importance of contextualizing ML-generated insights to ensure relevance and usability. Experts at Volvo Trucks point to the need for tools that seamlessly integrate ML into existing workflows, allowing design teams to navigate complex variables such as driver behavior, environmental factors, and real-time decision-making during driving. Published BIG FUN project work (Luo et al. 2024) further reinforces this perspective, noting that ML tools must bridge technical and human-centric considerations to empower designers effectively, rather than overwhelm truck development professionals with raw data or overly rigid models.

These requirements are reflected within the broader academic consensus on the potential of ML to transform the design process by automating routine tasks, predicting user behavior, and uncovering patterns that inform design innovation. Relevant academic knowledge also warns against a techno-centric approach that disregards the socio-technical context of design practices. Volvo Trucks domain experts echoed these concerns, emphasizing the necessity of human oversight and interpretability in ML applications. BIG FUN WP1 findings advocate for a dual focus: leveraging ML for efficiency while embedding explainability and adaptability into the tools. This dual approach ensures that ML insights are not only accurate but also actionable, fostering collaboration between AI and human designers and enabling scalable innovation in truck HMI systems.

5.3.WP2: Machine Learning Technologies for Commercial Mobility

WP2 first focused on the acquisition and cleaning of a data lake for consumption of ML methods (D 2.1). The data lake consisted of data from 5 trucks driven during their ordinary transports at

different locations in Europe. The trucks were equipped with regular physical mirrors or Camera Monitor Systems, CMS, replacing the rear-view mirrors. The trucks were instrumented with a data logger that captured CAN data at 10 Hz as well as the opportunity to save video from a camera on the dashboard looking at the road ahead of the vehicle.

To avoid storage issues and to obtain segments where a potential overtake occurs, we defined a precondition trigger, so the data logger only records when certain preconditions are met. Such an automatic trigger was designed by Volvo based on the values of some signals representative of potential overtake maneuvers. They included for example the activation of the left indicator combined with distance to the vehicle ahead. When the trigger is activated, the logger saves the CAN data from 20 seconds before the trigger up to 45 seconds thereafter. The files were later verified and labeled manually by Volvo from watching the videos and determining if a recorded segment is an overtake or not. Typical photos of an overtake and alternative non-overtakes (false positives) are shown in Figure 6.

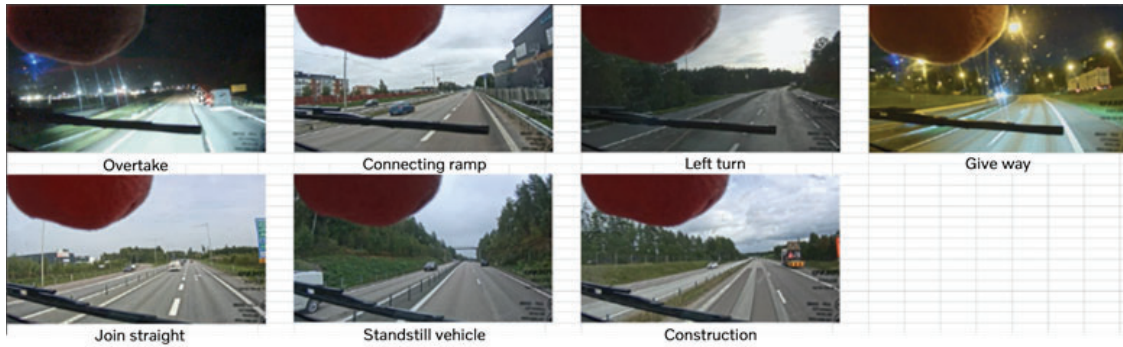


Figure 6: Images from truck footage exemplifying overtakes and non-overtakes

A second dataset was obtained by recording CAN data continuously during different driving sessions of the trucks. This dataset does not contain video data, so it remained unlabeled. As labeling would be a very time-consuming task, a pseudo-labelling technique was used.

The WP also focused on training and evaluation of ML classification methods (D 2.2) to predict identified moments of interest, i.e. overtakes. Prior to any development, extensive literature reviews were made on the use of ML with CAN data for automotive applications. We identified tasks regarding driver behavior analysis, driver intention, and even driver characterization (identity profile) based on driving habits. An important finding, however, was the scarce literature on truck vehicles, with most studies focusing on passenger cars. Findings of this literature study form the basis of a forthcoming survey paper on the topic.

In a subsequent stage, we compared three machine learning methods for the defined overtake use-case: Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM). These are based on different classification strategies and are a popular choice in the related literature on detecting vehicle maneuvers. We analyzed different parameters affecting the classifiers at the data preprocessing, preparation and training, and managed to obtain above 90% accuracy in detecting the positive (overtake) and negative (non-overtake) classes. See a table of the comparisons among tested classifiers in Figure 7, Class 0 represents non-overtake and Class 1 an overtake. The established ML-assisted classifier forms one result, and findings of this process were published in a conference paper at the 14th Scandinavian Conference on Artificial Intelligence SCAI 2024, and in a forthcoming extended journal paper.

	Label start at “trigger”		“trigger” – 1 sec		“trigger” – 2 sec	
Model	Accuracy (Class 0)	Accuracy (Class 1)	Accuracy (Class 0)	Accuracy (Class 1)	Accuracy (Class 0)	Accuracy (Class 1)
LSTM	0.821	0.892	0.792	0.961	0.717	0.933
Random Forest	0.755	0.987	0.745	0.987	0.720	0.987
SVM	0.773	0.973	0.760	0.973	0.722	0.973

Figure 7: Compared classifiers to predict overtakes & non-overtakes

Finally, we experimented with a deep-learning based classifier based on Long Short-Term Memory (LSTM) networks. These methods are known to be data-hungry, which was satisfied by using the previously mentioned continuous but non-labelled dataset as training data augmentor. This was done by employing the previously developed and selected ML classifier (SVM, RF) to pseudo label the continuous data. Then, the corresponding samples with very high or very low classification scores were included as training data of each class. By doing so, we expect to increase the classification accuracy of the classes even further. The established two step procedure forms another area for continued research, that is the one of: 1) developing an ML-assisted classifier of high quality to label the events of interest, and 2) applying this labelling classifier on larger amounts of non-labelled data to identify events for further ML-assisted analyses.

5.4.WP3: UX Design for ML-Powered Commercial Mobility

User experience (UX) design principles played a pivotal role in the BIG FUN project, aligning with FFI's (Strategic Vehicle Research and Innovation) overarching goals of fostering sustainable, safe, and efficient road transport. This work package focused on creating human-centered interfaces and workflows to effectively integrate machine learning (ML) insights into commercial vehicle design. These efforts directly supported FFI's mission to promote innovation in vehicle design while addressing the challenges of modern mobility.

A key focus of the UX design efforts was ensuring transparency and explainability in human-ML interactions. By providing clear explanations of ML outputs, including details about data sources, algorithm logic, and real-world examples, the project aimed to empower truck design professionals to make informed design decisions. This commitment to transparency directly supports FFI's emphasis on safety and efficiency by reducing risks associated with unclear or poorly understood ML outputs.

The tools developed in WP3 were designed to foster collaboration between human experts and ML-generated insights. By enabling dynamic interactions, such as adjustable filters, algorithm tuning, and the ability to validate "corner scenarios", the tools ensured that automation complemented human expertise. This approach aligns with FFI's focus on leveraging innovative technologies to create adaptable and sustainable solutions that enhance, rather than replace, human oversight.

Recognizing the diversity of expertise among users, the design incorporated adaptive explanations tailored to different levels of technical proficiency. As users gained familiarity with

the tools, explanations evolved to match their growing understanding. This inclusivity aligns with FFI's mission to engage multidisciplinary teams and empower stakeholders across the design process, from engineers to usability experts.

A scenario-centric approach was a foundational principle of the design. ML-generated insights were contextualized within specific operational scenarios, such as overtaking maneuvers. This focus on real-world applicability ensured actionable outputs that addressed practical challenges in truck human-machine interface (HMI) design. The iterative participatory prototyping process was critical to the project's success. Early prototypes explored core functionalities, while subsequent versions integrated detailed user feedback to refine the tools further. This user-centered approach reflects FFI's commitment to fostering knowledge transfer and ensuring that innovations remain relevant and practical for industry stakeholders, particularly within the Swedish automotive sector.

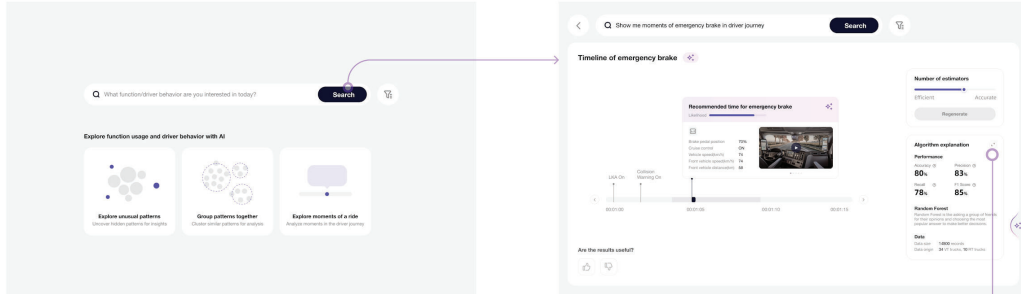
The deliverables of WP3 included interactive prototypes that emphasized usability and trustworthiness while enabling users to explore, validate, and contextualize ML insights. Examples of these prototypes are present in WP4. These tools underwent evaluation with professionals from Volvo Trucks, ensuring their practical application and alignment with industry needs. The work package also produced actionable UX design principles for integrating explainable AI into mobility workflows, contributing to FFI's vision of positioning Sweden as a global leader in sustainable and innovative transport solutions.

By integrating AI-driven insights into collaborative workflows, WP3 demonstrated how user-centered design principles could address FFI's goals of advancing safety, sustainability, and efficiency in road transport. This work laid a strong foundation for scalable innovations in the Swedish commercial mobility sector, underscoring the value of combining human expertise with cutting-edge AI technologies.

5.5.WP4: The BIG FUN Demonstrator

WP4 focused on the development and presentation of the BIG FUN demonstrator, a tangible proof-of-concept tool designed to showcase how machine learning (ML) insights and user experience (UX) principles can transform the design of commercial vehicles. This demonstrator embodies the culmination of research and development efforts across the project, providing stakeholders with a hands-on experience of the potential applications and benefits of integrating ML-driven insights into vehicle design workflows. An overview of the demonstrator is presented in figure 8.

- 1 Search for function/driver behavior of interest. In this example, we search "moments of emergency brake in driver journey".
- 2 Show moments of the target function/driver behavior with brief explanations.



- 3 Expand the explanation to access more explanations of the algorithm logic, model performance, data summary, and original data examples.
- 4 Hover on texts to tune the explanations.

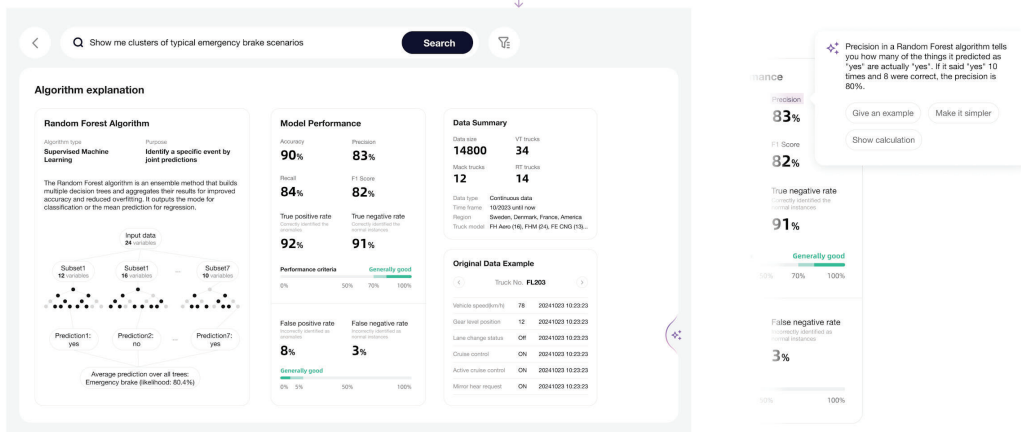


Figure 8: The BIG FUN Demonstrator

The demonstrator was crafted to illustrate key functionalities, such as the ability to identify and explain moments of interest during truck journeys, contextualize ML-generated outputs with user scenarios, and support designers in exploring and validating data-driven insights. By translating complex data into accessible, actionable formats, the BIG FUN demonstrator highlights how AI-powered tools can enhance safety, efficiency, and innovation in the commercial mobility sector.

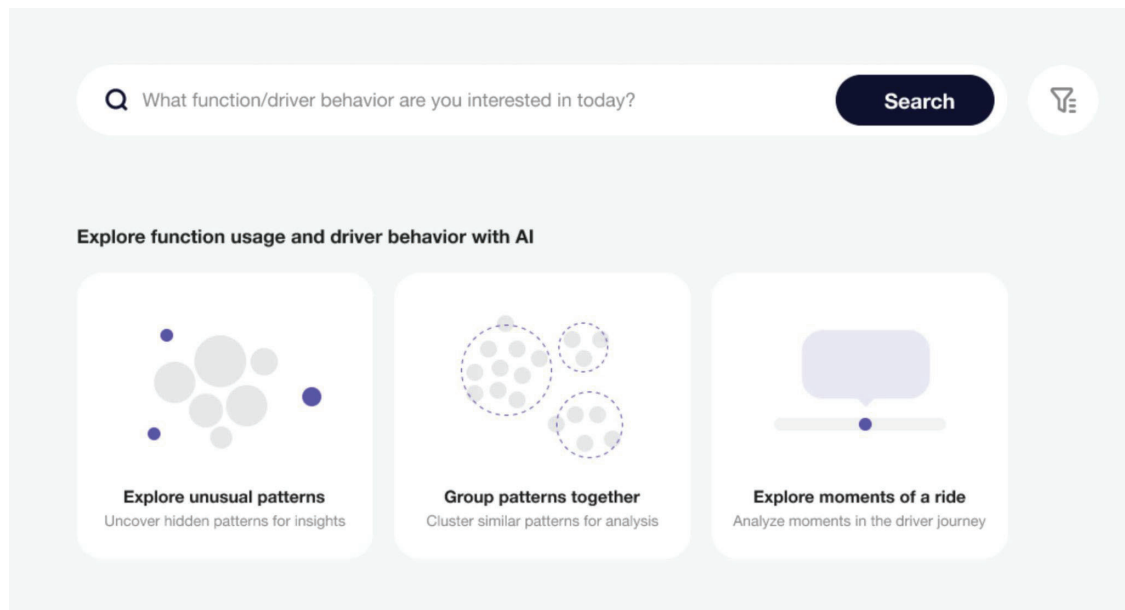


Figure 9: the BIG FUN Demonstrator Landing Page

The demonstrator landing page (figure 9) affords users with a search functionality, and three types of support: exploring unusual patterns in truck datasets to find inspiration for improving trucks, a grouping of patterns within specific truck functionalities, and explorations of moments of truck rides in a timeline. We include more figures and short explanations of some of these features below. A full conference paper on the BIG FUN demonstrator is accepted for publication at HCI International 2025, with a second paper planned to be finalized by summer of 2025. A filtering function (figure 10) is designed to enable human experts to target ML-generated insights by specifying key parameters that are of relevance to their interests. These parameters include data from available CAN data and filtering by vehicle type, road context and others.

Figure 10: Filtering function of the BIG FUN Demonstrator

The BIG FUN demonstrator allows users to see patterns in vast datasets by grouping data into clusters of relevance. A Large Language Model (LLM) component is used to generate names for these clusters, (for instance “clusters of emergency brake” as seen in figure 11). The LLM naming can be edited by the user. Users can also change parameters of the algorithm to tune results to match their interest.

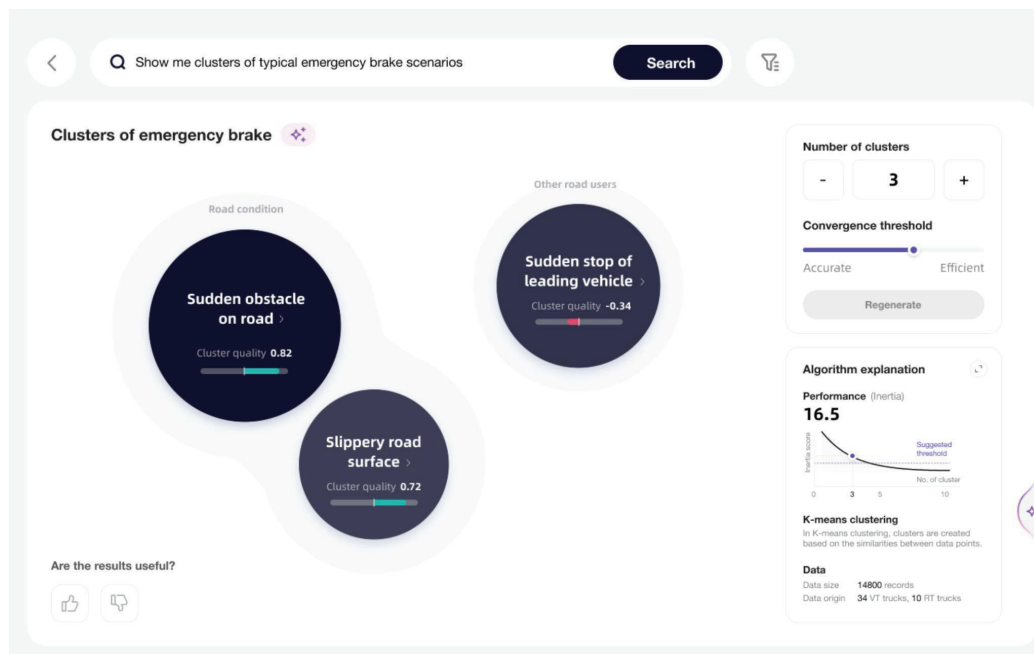


Figure 11: The clustering function of the BIG FUN Demonstrator

Another functionality is named “explore moments of a ride”, where users can see a ML-generated timeline that summarizes patterns of truck behavior around a topic of interest that users have typed in, in a time sequence. In the example in figure 12, a human expert has generated a timeline of when the emergency braking system has activated in truck journeys. An LLM system has generated names for the timeline, highlighted by the purple AI icon, and on the left of the screen there is a possibility to tune the algorithm, and to see a short explanation of the algorithm’s performance and way of working.

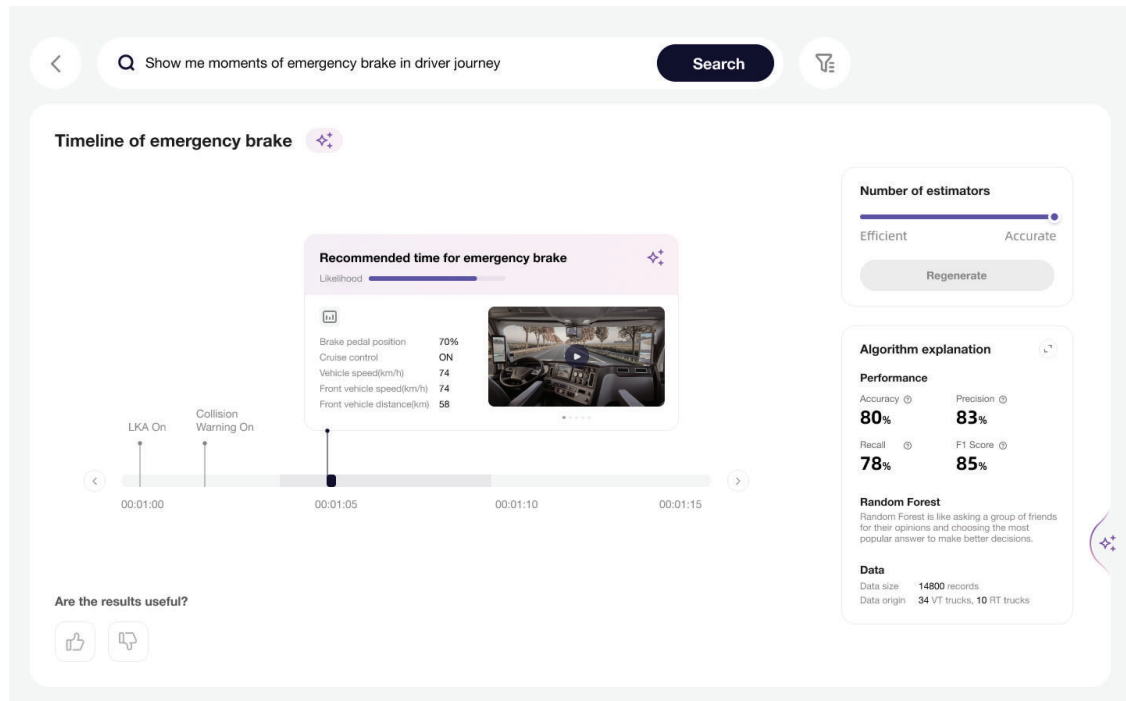


Figure 12: BIG FUN Demonstrator timeline feature.

Another functionality is connected to explanations, designed to provide transparency for how the BIG FUN demonstrator works for the users that are interested. Explanations are organized in three categories, each represented by a card, as seen in figure 13. From left to right, there is a simplified explanation of the algorithm model used. In the middle there is an explanation of the model’s performance, designed to help human experts comprehend the algorithm and calibrate their trust towards the algorithmic results. On the right, there is a card that provides information and examples of the dataset used to produce the prediction that the algorithm has generated.

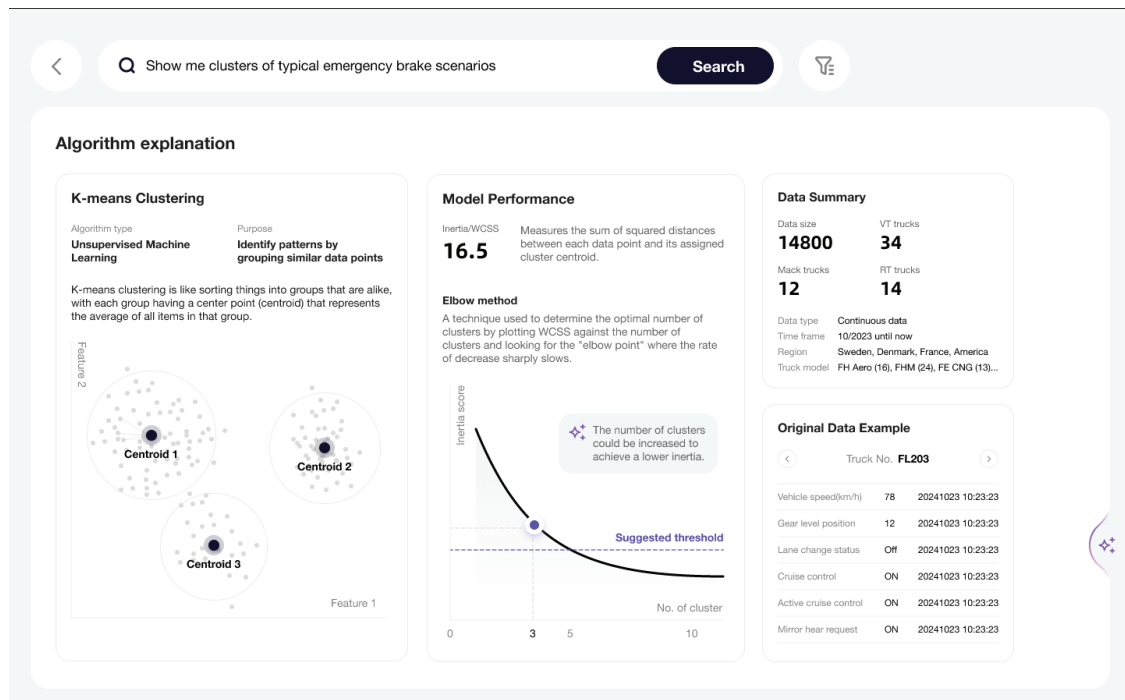


Figure 13: BIG FUN Demonstrator Explanations Screen

6. Benefits for Industry

The BIG FUN project has provided valuable insights into how AI and ML can be applied to identify driving events, characterize their features, and understand the sequence of events before, during, and after they occur. However, the importance of thoroughly checking and cleaning data before applying advanced methods has been emphasized, as different types of data hold varying levels of information.

This project has taken a broad approach, exploring not only the application of AI/ML methods for data analysis but also how the resulting insights can be conveyed effectively to professionals across diverse product development disciplines. Although the scope of the project was limited, it successfully indicated and exemplified potential applications, particularly emphasizing the need for an ML-assisted labeling function to identify specific events of interest. Extending this work to use ML for describing and predicting behaviors surrounding these events offers significant potential.

Future efforts should aim to refine and generalize this two-step approach to make it applicable to a wider range of events and scenarios. By leveraging AI/ML to analyze functions with direct customer relevance, which often involve expertise from multiple product development disciplines, these technologies can foster a better collective understanding and increase the usability of available data.

To prepare the demonstrator tool for industrial implementation, it will be crucial to enhance the AI-assisted explainability of real-world events by involving subject matter experts from various disciplines relevant to product development. By focusing on a small but diverse set of events and functions, the tool's quality can be further improved, ultimately enabling its application to a broader range of events and functions commonly explored in product development processes.

7. Dissemination and publications

7.1. Dissemination

How are the project results planned to be used and disseminated?	Mark with X	Comment
Increase knowledge in the field	x	Publications during and after BIG FUN increase knowledge of using AI technologies in design for trucks.
Be passed on to other advanced technological development projects	x	Knowledge from BIG FUN is planned to be used in upcoming research funding applications within the field of mobility
Be passed on to product development projects	x	Results from BIG FUN are used to further data-driven work in Volvo Trucks
Introduced on the market		
Used in investigations / regulatory / licensing / political decisions		

7.2. Publications

BIG FUN work has produced peer-reviewed published work, as well as manuscripts that are being developed and are planned to be published in the near future. These papers and manuscripts are described in the sections below.

Design Conference Paper

The paper *"Navigating from Data-Driven Design to Designing with ML: A Case Study of Truck HMI System Design"* explores the integration of machine learning (ML) in truck human-machine interface (HMI) design, addressing the challenges and opportunities of incorporating data-driven tools into the automotive design process. Through a case study with a large commercial truck manufacturer, the authors highlight decentralized data practices, the critical role of human expertise in decision-making, and the untapped potential of ML to enhance HMI system design. Findings emphasize the need for context-customized ML models and tools that align with industry workflows while respecting the complexities of truck design, including safety regulations, user variability, and multimodal interactions. The study concludes with actionable insights for advancing human-ML collaboration in HMI design, emphasizing the importance of

integrating technical capabilities with socio-technical considerations to create effective, scalable solutions. This is a published paper (Luo et al. 2024)

ML in UX literature review

The paper *"Using Artificial Intelligence to Support User Experience Design: A Systematic Literature Review"* examines how artificial intelligence (AI) technologies are being utilized to enhance user experience (UX) design practices. By analyzing 83 empirical studies, the authors identify key applications of AI across the UX design process, including predictive tools for data analysis and usability testing, as well as generative systems for ideation and prototyping. The findings highlight a shift from technical-centric AI development to human-centered approaches that balance efficiency with creativity, while addressing challenges such as over-reliance on automation and the need for explainable AI. The review underscores the potential for AI to augment the UX design process, especially through adaptive tools that support diverse design activities, and provides a roadmap for future research to develop AI-enabled tools that align with human-centric values and design thinking principles.

UX for Explainability of ML in commercial mobility paper

The paper *"Expectations for Explainability in an AI-Powered Data Analytics Platform for UX Design"* investigates the role of explainability in fostering effective human-AI collaboration within the context of truck human-machine interface (HMI) design. By studying UX designers' interactions with an AI-powered data analytics prototype, the authors identify critical factors influencing the usability and trustworthiness of AI explanations, such as tailoring explanations to the user's technical expertise, contextualizing outputs with real-world scenarios, and adapting explanations dynamically as user proficiency evolves. The findings emphasize the sociotechnical nature of AI explainability, highlighting the importance of moving beyond purely technical descriptions to focus on actionable, user-relevant insights. This work contributes to the growing body of research on human-centered AI by providing practical recommendations for designing explainable systems that enhance agency, trust, and collaboration among diverse stakeholders in complex design environments.

Predicting Overtakes in Trucks Using CAN Data

Conference paper published at the 14th Scandinavian Conference on Artificial Intelligence SCAI 2024. The paper investigates the detection of truck overtakes from CAN data. Three classifiers, Artificial Neural Networks (ANN), Random Forest, and Support Vector Machines (SVM), are employed for the task. Our analysis covers up to 10 seconds before the overtaking event, using an overlapping sliding window of 1 second to extract CAN features. We observe that the prediction scores of the overtake class tend to increase as we approach the overtake trigger, while the no-overtake class remains stable or oscillates depending on the classifier. Thus, the best accuracy is achieved when approaching the trigger, making early overtaking prediction challenging. The classifiers show good accuracy in classifying overtakes (Recall/TPR $\geq 93\%$), but accuracy is suboptimal in classifying no-overtakes (TNR typically 80-90% and below 60% for one SVM variant). We further combine two classifiers (Random Forest and linear SVM) by averaging their output scores. The fusion is observed to improve no-overtake classification (TNR $\geq 92\%$) at the expense of reducing overtake accuracy (TPR). However, the latter is kept above 91% near the

overtake trigger. Therefore, the fusion balances TPR and TNR, providing more consistent performance than individual classifiers.

Machine Learning for CAN Bus Data

Journal paper under preparation regarding the ML literature review. The paper provides an overview of the domain applying Machine Learning (ML) to in-vehicle controller area network (CAN-BUS) sensor data. These domains include Driver Behavior Identification, Driver Intention Analysis and Driver Identification.

Machine Learning for Predicting Overtakes in Trucks Using CAN Data

Journal paper under preparation extending results of the SCAI paper above. The paper increases the amount of data previously available in the conference paper, including extra trucks. We also do a systematic evaluation of different parameters affecting data preprocessing, preparation and training of ML methods, which in the SCAI paper were fixed based on previous literature. In addition, we provide insights on the difference in CAN data between overtakes and non-overtakes.

Paper on CAN data pseudo-labelling and deep-learning ML methods

Paper under preparation detailing experiments on pseudo-labelling of continuous data and application of a deep-learning based classifier based on Long short-term memory (LSTM) networks. At the time of writing, many of the experiments are running before access to Volvo data is finished when the project ends, leaving its interpretation and analysis for later, when the publication will be written. It will potentially address a journal.

8. Conclusions and future research

The BIG FUN project demonstrates how machine learning (ML) technologies and user experience (UX) design can collaboratively transform the development of commercial vehicle systems. By integrating advanced data analytics with qualitative insights, the project focused on identifying critical moments in truck journeys, such as overtaking maneuvers, and translating these insights into actionable knowledge for system designers. Key deliverables include a demonstrator platform that enables human-AI collaboration, facilitating transparent and explainable ML-generated insights that align with professional workflows. These outcomes not only advance the safety, efficiency, and sustainability of truck designs but also set a foundation for scalable applications across various commercial mobility challenges. Future work should build on these achievements by expanding data sets, refining ML methodologies, and exploring broader use cases to further bridge the gap between innovative technology and practical industry applications.

The ML experiments were based on CAN data representative of overtakes. There is potential to assess the impact and utility of each signal, to improve signal inclusion or exclusion. Performance inconsistencies among trucks highlight the need for larger labeled datasets to enable cross-truck studies, simulating real-world applications where systems encounter new drivers. Underutilized

continuous data presents opportunities for pseudo-labeling, clustering overtakes, and exploring predictive insights on driving patterns, safety, and traffic flow. Beyond overtakes, the approach could extend to diverse maneuvers like parking or turning, emphasizing ML's role in identifying patterns and supporting predictions. Lastly, industrializing the ML demonstrator tool through expert involvement and iterative development could integrate it into product workflows, enhancing the quality of human-AI interactions.

Artificial intelligence technologies hold a lot of promise, but the novelty and current popularity of AI makes it challenging to ascertain where AI can truly contribute to improving truck technologies, and where AI is just the latest hype. AI technology must be designed in a way that is understandable to users for it to have value (Ehsan et al. 2021; Amershi et al. 2019; Wang et al. 2020). Further issues of algorithmic bias have been recognized in relevant work (Hajian, Bonchi, and Castillo 2016) and in BIG FUN work (for instance in a forthcoming paper on the design and evaluation of the BIG FUN demonstrator) must be addressed for this technology to be trustworthy.

Building on results from the BIG FUN project, there is great potential in exploring and understanding how descriptive (non-AI) and predictive data analytics can be designed to support human-technology collaboration in the design of systems and services for truck systems design. Future work should contain iterative UX design work that will match data-driven (descriptive) and ML-powered (predictive) analytics to the needs and practices of truck systems development teams, enabling a deep understanding of driver behavior to optimize functionalities and related HMI solutions.

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