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# Navigating from data-driven design to designing with ML: a case study of truck HMI system design

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**Abstract**

Data-driven design is believed to be empowered by machine learning (ML) with advanced pattern classification and prediction. However, research on how ML can be used to support automotive human-machine interface (HMI) design is lacking. We presented a case study of truck HMI design to understand the current data use and expectations of ML in the design process. Findings show decentralized data practices, the role of expertise in decision-making, and the envisioned reactive use of ML, where we underscore the implications for advancing human-ML collaboration in designing future truck HMI systems.

*Keywords: data-driven design, design process, machine learning, truck HMI, ML user needs*

## 1. Introduction

Data-driven design has been a common practice of using data to support design decision-making, where data is collected and analyzed to unveil user behavior and evaluate design solutions (Bertoni, 2020). Machine learning (ML) empowers data-driven design with advanced pattern classification and prediction based on historical data (Wang *et al.*, 2022). A growing body of design research has applied ML to automate mundane tasks and predict user experience by quantitative persona creation (Salminen *et al.*, 2020), design generation (Gajjar *et al.*, 2021), and automated product evaluation (Wang and Liu, 2021), primarily focusing on the context of software applications.

Despite the increasing interest in supporting the design process with ML, there is a lack of research on how ML can be used to support interaction design in the automotive context. In this paper, we focus on truck human-machine interface (HMI) design, which refers to the design of in-vehicle interaction between drivers and trucks. The in-vehicle interaction encompasses the interaction with both digital and physical interfaces through multimodalities such as vision, auditory, and haptics. Rooted in hardware, commercial trucks have progressively incorporated infotainment systems and other in-cab systems that support rich functionalities such as voice assistants, resulting in a blended experience of digital and physical interaction. Typically, truck HMI design faces the challenges of handling unpredictable internal factors (e.g.: driver experience level) and external factors (e.g.: lighting conditions) that impact how drivers interact with trucks (François *et al.*, 2017). Although ML has the untapped potential to enhance the understanding of driver journeys, ML technologies have primarily been applied for tasks such as driver assistance, predictive maintenance, and autonomous driving (Theissler *et al.*, 2021; Vaughan and Wallach, 2021), highlighting the knowledge gap regarding ML-empowered truck HMI system design.

In this paper, we explore today's data practices and the expected use of ML in the truck HMI design domain. ML models seldom reach industry practice due to a lack of context customization (Lu *et al.*, 2022). Therefore we positioned our research in the context of one large commercial truck manufacturing organization to gain in-depth knowledge of how data was used in the design process and identify opportunities and design implications of how ML could contribute. We conducted semi-structured interviews with eight experts from different roles in the truck HMI system design process. Our work contributes to (1) unpacking how and why human experts use data to support decision-making in the context of truck HMI system design, (2) highlighting experts' expectations and design opportunities of how ML could be used in the truck HMI design for future research and industry applications, and (3) potentially informing design implications of ML-empowered design tools and organization-wise preparations for data infrastructure and workflow renovation to empower the design process with ML.

## 2. Related work

### 2.1. Data-driven design in the era of ML

ML is defined as a set of methods that "*can automatically detect patterns in data [...] to predict future data or to perform other kinds of decision-making under uncertainty*" (Murphy, 2012). The generative and predictive capabilities of ML are believed to empower data-driven design with automated design generation and predictive analytics that uncover user behavior patterns and inconsistency (Lu *et al.*, 2022). Facing the identified opportunities, an increasing number of studies have focused on developing ML-empowered design tools. Much of the research in this field was devoted to evaluating the cognitive, affectional, and behavioral aspects of user experience, such as cognitive workload and usability analysis (Bozkir *et al.*, 2019; Fan *et al.*, 2020). Another trending research topic is automated design generation where researchers have engaged deep learning neural networks and object detection algorithms to generate UI wireframes for a given UI design pattern (Gajjar *et al.*, 2021), translate text description to UI mock-ups (Huang *et al.*, 2021).

However, there still seems to be a gap between the research impact of ML-empowered design tools and industry practices (Jiang *et al.*, 2022). Challenges of adapting ML-based tools not only exist in the costly implementation and ethical issues of data collection, but also the absence of a sociotechnical perspective that considers the context of human designers supported by ML. Current AI/ML-based research is more techno-centric (Ehsan *et al.*, 2021), raising concerns about its potential negative effects (Shneiderman, 2020). Current ML models rarely go beyond graphic interface assistance, and even these automatic interface generation tools require excessive effort to customize the ML-generated non-context-specific results (Lu *et al.*, 2022). Situated in the context of truck HMI design, our work aims to develop a grounded understanding of how industrial practitioners currently work with users, data, and technology, and then identify where/how ML-empowered tools can potentially contribute.

### 2.2. Data-driven design in the automotive industry

The digital transformation of automobiles provides useful insights for the design of truck HMI systems. In both automobiles and commercial trucks, product design involves long, complex development cycles encompassing safety regulations and manufacturing constraints. The automotive industry's roots in hardware bring challenges (Ebel *et al.*, 2021) of data availability: (1) automotive software platforms not designed for data collection, (2) data separated among multiple subsystems and external suppliers, and (3) data protection regulations.

Despite these challenges, designers in the automotive industry have expressed particular interest towards integrating data into the design process (Ebel *et al.*, 2021). User interaction data could decrease the impact of conjecture and guesswork in the consumer vehicle design process (Ebel et al., 2020) through data-driven personas, content-dependent design evaluations, and user flow visualizations (Ebel *et al.*, 2021).

The value of ML In extracting valuable insights from data to support decision-making in the automotive industry has been recognized but practiced to a limited extent. Yadav and Goel proposed a mathematical framework to relate customer satisfaction level to component-level product requirements, such as interior quietness (Yadav and Goel, 2008). Another example is an ML-based vehicle silhouette design system that auto-generated the vehicle design based on user selection (Usama *et al.*, 2021). However, most research related to AI/ML in automobiles has focused on integrating AI/ML in vehicles: autonomous driving (Yurtsever *et al.*, 2020), driver assistance (Joshi *et al.*, 2019), and predictive



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maintenance (Theissler *et al.*, 2021). There is scant attention on developing ML-empowered tools for automotive design practitioners, and exclusion of the socio-technical aspect of where and how the tool could fit in or change the vehicle design process. This paper is intended to contribute to this gap by describing a user study grounded in design experts' real-world practices, understanding what is the current status of data usage in truck HMI design, and identifying the underlying needs, opportunities, and design implications for ML-empowered design tools.

# 3. Methodology

## 3.1. Study procedure

This case study focused on the design of HMI systems at one large commercial truck manufacturing organization with over 10,000 employees globally. We conducted in-depth semi-structured interviews with eight industrial experts, 87.5% of whom have more than 7 years of experience in truck HMI design. Participants were recruited by direct contact and snowball sampling and the sample size followed the principle of data saturation (Guest *et al.*, 2020; Parker *et al.*, 2019). Participants have been anonymized and are referred to by ID (P1-P8). Participants' job roles are product design (P1, P3), user experience design (P2, P5), engineering (P4, P8), strategy management (P6-P7).

The interview was structured into three parts: 1) role and experience, 2) data usage in the current product design process, and 3) future expectations of ML-empowered product design. The first part gathered information on the participant's role and daily routine. In the second part, the researchers introduced an empty canvas which divided the product design process into several phases. The purpose of the canvas was to ground the interview in real-world practice, collecting what and how data are used in different stages of the truck HMI design process. Each participant was asked to pick a released product function as an example. The researcher and participant walked through the design process of this selected function together, recalling lived experiences and filling the canvas accordingly. In the third phase, participants shared reflections and future expectations of data and ML-empowered product design. The interviews were conducted online, video recorded, and transcribed. Each interview took 60-75 minutes.

## 3.2. Qualitative analysis

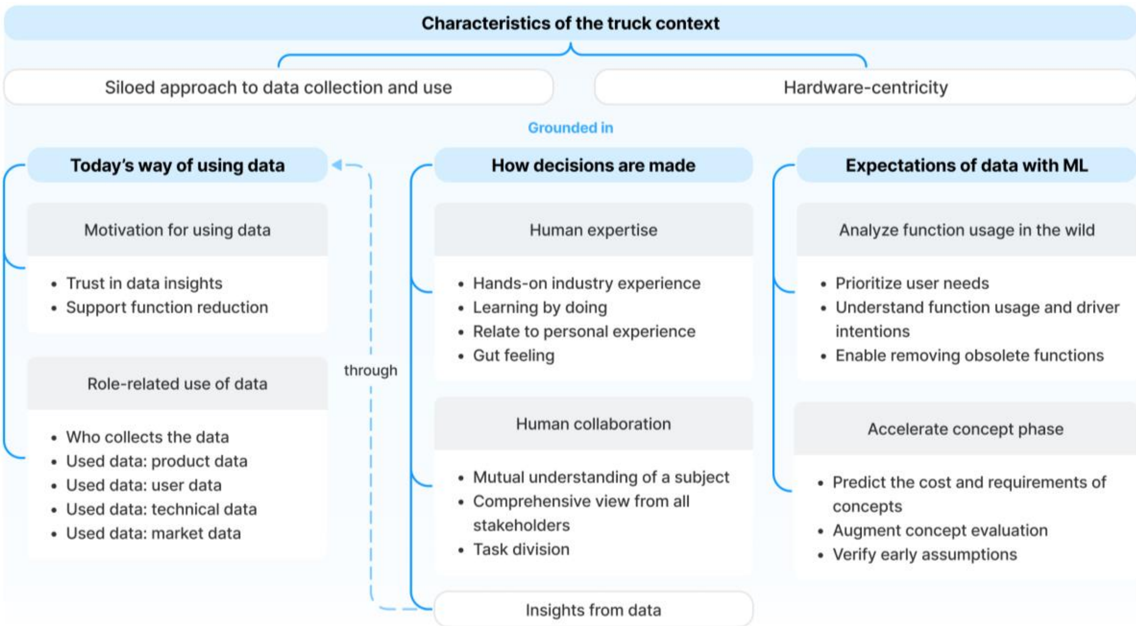


**Figure 1. An illustration of codes and categories from the thematic analysis**

A thematic analysis of the interview transcript was done, following the process of open coding, axial coding, and selective coding with backward iterations when necessary (Clarke and Braun, 2017). Firstly, two authors tagged segments of transcriptions related to data usage with a descriptive code name using



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the tool Atlas.ti. The purpose was to identify any piece of valuable information. Secondly, one author reviewed the highlighted codes and notations, merging connected codes and constructing categories. Thirdly, the authors reviewed the codes and categories collaboratively, and built core categories and propositions by grouping previous categories. Figure 1 illustrates the developed core categories and codes, which reflect today's way of data use and decision-making, and future expectations of ML permeated by characteristics of the truck HMI context.

## 4. Findings

The study investigates data usage and future expectations of ML situated in the truck HMI design context, taking an organization as a case study. During the interviews, we identified two characteristics of the context underlying current use and future use of data. The first characteristic is hardware-centricity, featuring a lengthy verification process in pre-production vehicles, high manufacturing costs, long feedback loops, and dependency on previous hardware versions, as exemplified by P5: "*Let's say we wanted a new digital instrument cluster. You can change the software and graphics. But if we wanted a bigger cluster, then it's a big change."* The second characteristic is the siloed approach to data collection and use. While truck functionalities are distributed and carried out by multi-stakeholder teams, each team conducts its own data collection and use, as opposed to having a centralized process and repository of data, making it harder to recycle data and "*gain a holistic view of truck usage*" (P6).
The two characteristics of hardware-centricity and siloed approach to data collection and use permeate the key themes that emerged during the interview analysis and inform the organization's trajectory of integrating advanced data collection and use in the truck HMI design process. In the sections below, we present key themes of data practices and identified opportunities for ML.

### 4.1. Decentralized practices inform data use

Data collection and use was centered on specific projects and concerns of specific job roles within the company, following unspoken rules of who collects and uses what type of data. During the qualitative analysis of the interviews, four different subsets of data emerged, with each subset connected to a particular job role. Product data, such function specifications and context of use, are collected and used by product designers to determine if a function fulfills the intended requirements or behaves as expected. This data may also be used by UX designers, engineers, and strategy managers. User data such as understandability, usability, effectiveness, satisfaction and function usage are the primary focus of UX designers, but are also relevant to product designers and strategy managers. Technical data such as speed, acceleration, steering wheel angle and pedal pressure are provided by sensors in the truck and is acquired by engineers. This type of data may also be needed by product designers and strategy managers. The final data type, market data such as return on investments is of relevance primarily to strategy managers.
Decentralized data practices lead to the division of resources for collecting and processing data, and dependence on other stakeholders to provide necessary data. On the other hand, decentralization allowed relevant stakeholders to directly engage in data collection and use, leading to bespoke and contextually relevant data-driven insights. Also, the engagement in acquiring data was considered a valuable learning process by the participants as it enhanced the understanding of the product maturity.

### 4.2. Data to support high-stakes decisions

Another recurring theme we discovered is that participants sought a sense of confirmation from data to support the decision-making process, as a counterbalance to typical long cycles of collecting user feedback in truck HMI design. There is a tension between participants' desired level of caution for decision-making and the restricted time frame. P6 expressed his hesitation about function removal when having to wait approximately nine months before acquiring feedback. P8 noted that the irreversibility of hardware further increased the stress of decision-making. With the desire to avoid mistakes, P6 had to endure uncertainty when lacking confidence in a decision and would like to rely on data for support: "*I would be much more comfortable if we had more numbers from vehicles on it.*" The same needs were expressed by other participants when they referred to data as "*structured*" and "*objective*" information



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that confirmed existing assumptions and provided more confidence in decision-making. The perceived objectivity of data indicated participants' strong need for factual support to cope with the anxiety of uncertainty in the design process.

## 4.3. Human expertise and collaboration are key in decision making

Human expertise enabled balancing user needs and practical constraints, assessing product feedback, and making decisions in the design process. This expertise was cultivated by substantial hands-on experience that allowed participants to "*jump into the users' clothes*" (P1). Learning by doing also helped P2 gain more knowledge of product strategy along the design process. Besides, participants related their personal experience to product design to feel closer to user needs. One common way was to experience the truck first-hand to develop their own interpretation of functionalities (P1, P3, P5). Another way was to work with a subject closer to one's daily life. P1 felt designing the sound system he used every day in his own car was useful, since he "*could relate to the end users in a better way.*"

Based on human expertise, participants could evaluate the importance of user feedback by sifting through the data and ditching the noise. Expertise enables designers to down-prioritize some user feedback regarding less severe issues for the benefit of the overall project.

Gut feeling, cultivated by years of experience, could be the deciding factor in tough decisions. P6 noted that decision-making is "*not a precise science,*"; with all the factual data presented, "*it still requires some gut feeling and [previous] experiences.*" Due to the siloed way of data collection and use, truck HMI experts became the critical carriers of specialized knowledge and conveyors of experience.

Human collaboration is another critical component in decision-making. Human collaboration allowed participants to align "*the expectation of the project*" (P6), "*limitations on design solutions from different perspective*" (P3), and "*pros and cons of different ideas*" (P7) to avoid rushing into a reckless decision. Three aspects of productive collaboration that required handling with sensitivity were mentioned by the participants. Firstly, it was crucial to maintain a mutual understanding of the subject between the stakeholders from different roles and backgrounds. P2 recalled an instance where all stakeholders agreed on the design but a missed detail was implemented in an unexpected way due to different interpretations. Secondly, it was crucial to involve stakeholders from each role to gain a comprehensive view when making a decision, as each stakeholder represents the knowledge of their domain. Finally, participants treated the task division delicately to avoid overstepping the boundaries of responsibility in human collaboration. For example, P2 noted "*I would make the proposal on a really high level, not to take anybody else's role.*"

## 4.4. Expectations of data with ML

In the final phase of the interviews, participants envisioned how ML can help deliver value through a deeper understanding of data.

### *4.4.1. ML for analysis of function usage in the wild*

As user needs were currently prioritized based on the criticality of the need, required investment, and estimated values, participants envisioned ML to complement a user-centered perspective on user needs prioritization. The desire behind this expectation was a concern of devoting resources to develop less-used functions and a hope that ML would help manage priorities as project parameters shifted during the design work. P1 pictured ML to generate a priority list rated according to what was important to the users, an opinion also reflected by P4.

Participants stated that continuous data gathered from trucks on the road can help understand function usage and driver intentions. Participants preferred "*number-based*" (P1) and "*measured data, like logging speed*" because it was perceived as "*structured data*" and easier to process. The need for continuous data came from participants' desire to inform design work by learning "*how users actually use our functions and sub-functions*" (P3) which they currently did not have access to. Understanding the motivation behind function use was of equal significance to the participants, whether the less-used function stemmed from a lack of usefulness or misinterpretation of user needs.

Participants expected ML-supported understanding of function usage and driver intention to enable removing obsolete or redundant functions inherited from previous generations of trucks. Removal of



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functionality was especially challenging due to the concern of users' negative reactions (P2). P6 pointed out the trend in the automotive industry moving towards "*more and more automated functions*." P2 believed the insights from continuous data could reveal function usage from a larger population of vehicles, building up participants' confidence to remove or automate redundant functions, eventually, designing more intuitive, customized, and context-aware functions.

#### *4.4.2. ML for accelerating concept evaluation*

Six of the 8 participants named the concept phase as the top process they wanted to change with ML. The concept phase is the stage that decides the direction for future design and implementation, including activities such as concept evaluation, which was constantly limited by time and resource constraints. Exploring the concept phase sufficiently requires accelerated efficiency from ideation to evaluation.

A first expectation for ML was having evaluative predictions on the cost of developing and deploying concepts, as cost impacts which concepts get to be developed. For instance, P7 expected ML to predict cost and requirements based on the concepts selected by the design team. P8 envisioned the ML tools as helpful support for early-on feasibility estimation that is "*quick to judge the difficulty or even generate early-on code to speed up or make it easier to do.*"

A second expectation was for ML to augment the concept evaluation with "*more data and speed*" (P6) and "*more frequency*" (P5). P6 stated that a faster pace than the usual six-plus months may keep projects fresh in people's minds and thus keep stakeholders more engaged in projects.

Finally, participants envisioned that insights generated by ML from real driver usage could challenge assumptions and verify design decisions. P3 would like to be "*freer and more flexible to implement alternative solutions*". P6 would base decisions on "*quicker testing and quicker loops to get quantitative data from different scenarios and applications*". With a background in design, P7 considered data as the most compelling evidence to substantiate a designer's perspective on user experience.

## 5. Discussion: Implications for use of ML in the design of HMI systems

This research found key gaps between expectations regarding the contribution of ML and the current use of data in the truck HMI design process. Participants envisioned ML to provide quantified insights to justify design decisions and drive design improvements. However, the contextual factors of decentralized data practices and hardware-centricity raise significant challenges for the implementation of ML practices. Also, how ML aligns with a design process that highly values human expertise necessitates consideration, which we will discuss in the following section.

### 5.1. Proactive versus reactive use of data

Our study presents truck HMI design-specific expectations of data and ML. Besides uncovering user behavior mentioned by previous work (Gorkovenko *et al.*, 2020), the truck HMI context places more emphasis on ML generating quantified and evidence-based insights that enable evaluation and prioritization activities to aid experts in high-stakes design decision-making.

Our findings show a pattern of reactive ML usage, to converge existing design alternatives to a specific decision through evaluation and prioritization, rather than to diverge the design space by identifying new design opportunities proactively. We transferred the proactive and reactive use of ML from a technical study in data mining: proactive ML prediction monitors changes actively, and a reactive prediction adapts to changes after detecting they took place (Yang et al., 2005). We propose that the reactive use of ML is related to: (1) participants use of data in the design process for its perceived objectivity, in response to an increasing need to convince their colleagues of user research findings with quantified results (Chromik *et al.*, 2020); (2) the organizational tradition of decentralized data practices which made data an important but rare resource that participants consult mostly for critical decisions rather than for open exploration; (3) current industry applications of ML in predictive maintenance (Theissler *et al.*, 2021) reinforcing the perceived affordance of ML towards pattern recognition and prediction.

To introduce ML as an active collaborator, instead of as supportive material, requires a shift in participants' mindset of data capabilities, organizational efforts in building data infrastructure, and



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diverse demonstrators of ML use cases. Although we found that participants saw numbers as unbiased truth, data itself is merely a value, which needs to be conceptualized in specific contexts (Feinberg, 2017). Our findings indicate the inherent value of designers engaging in data collection as a design activity, deciding what to collect and which scale to use, which helps designers to understand the intricacies of data nature, to work with instead of against the inevitable flexibility of data, and to conceptualize the data to suit specific objectives.

## 5.2. Keeping the organization in the loop

The decentralized data practices found in this study stress the need to prepare an organization for ML in terms of data infrastructure, ML customization, the situated task, and the affected organizational process. A successful ML integration needs the organization's practice and ML to be continuously aligned and co-evolved, keeping the organization in the loop (Herrmann and Pfeiffer, 2023).

As for data infrastructure, there exists a delicate balance between decentralized and centralized data practices. While centralized data practices bring the benefits of efficiency and unified data format, our findings suggest that decentralized data practices provide more context specificity, scalability, and local autonomy. With the benefits of centralized data practices widely accepted, we think it is important to keep a critical mind on two aspects. The first one is how to balance the varied perspectives and expectations of multiple stakeholders as participants showed varied interests in subsets of data. The second aspect is that the design of centralized data infrastructure needs to calibrate the intended level of specification of data. The more objective and specific the data is, the less room and ambiguity is left for the reconceptualization of the data (Feinberg, 2017). To fulfill present and future needs, the collected data should either cover enough details to enable diverse data use, or be bundled with sufficient contextual information to assist different practitioners in forming interpretations based on their expertise and their purpose.

## 5.3. Advancing human-ML collaboration in decision-making

Our findings indicate that decision-making involves the interplay of data, human expertise, and human collaboration. Human experts set objectives and assess the reliability of data inputs based on personal expertise and collective intelligence. Therefore, we highlight the need to empower human experts' competence and autonomy in human-ML collaboration, considering the facets identified as requiring sensitive handling within human collaboration.

### *5.3.1. Design for mutual understanding*

As participants noted mutual understanding among stakeholders is important to streamline interpersonal communication, maintaining a mutual understanding of ML among stakeholders is of equal importance. ML adoption might elevate the complexity since the channels of information exchange will be multiplied, exposing more risk of misinformation when interpreting and disseminating the insights from ML.

Facilitating effective communication between humans and ML requires efforts from both sides. On the one hand, designers need to acquire knowledge of ML, including the potential, complexity and the power imbalance embedded in ML (Mohamed et al., 2020), to avoid excessive trust in automation. On the other hand, the design of ML-empowered tools needs to open the black box by bringing in transparency and explainability, which supports designers in constructing their own sense-making and cultivating trust in. More research is needed to understand the context-specific dimensions of ML system transparency and explainabililty.

### *5.3.2. Design for human autonomy*

As task division is treated as a delicate process mentioned in the interviews, it is important to consider how integrating ML will impact existing power dynamics and human autonomy. Our findings on the irreplaceability of human expertise in the truck HMI design process highlight the significance of boosting human autonomy in human-ML collaboration. The call for a multi-faceted way to address autonomy has long persisted (Güldenpfennig *et al.*, 2019), viewing human autonomy as a context-



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dependent concept. In the context of truck HMI design, we realize participants' autonomy is partially reflected in one's freedom to explore and the power to decide. Hence, an ML-empowered tool should offer sufficient interactivity where designers could engage in exploring different settings, controlling the operation process, and tuning the generated results of ML. Future research could also investigate how the mentioned facets nuance the perceived human autonomy and what other facets underpin human autonomy in the context of truck HMI design.

### 5.4. Practical design implications

Our findings present a decentralized data practice where human expertise drives how data is collected, assessed, and interpreted to assist the decision-making process when designing truck HMI systems, and highlight experts' expectations of ML. For future work on integrating ML into the truck HMI design process, we stressed the following practical design implications to consider the social-technical context and avoid disempowering human experts:

- Importance of context: Integrating ML into the design process requires a highly contextualized understanding of designers' current way of working and the expected human-ML relationship.
- Organization-in-the-loop: It is critical to prepare an organization for ML and customize ML so that the organizational practice and ML could co-evolve.
- Role-related customization: Our research found a role-related interest in subsets of data, which potentially suggests a role-related preference for ML-generated output.
- Human autonomy: Due to human expertise's dominant role in truck HMI design, ML should be designed to enhance human autonomy to maintain the existing power dynamics and advance human-ML collaboration.
- Transparency & explainability: ML with transparency and explainability could help industrial experts understand the capabilities and complexities of ML, assess and form one's own interpretations of ML-generated insights to avoid excessive reliance on automation.

### 5.5. Limitations & future work

Our study provides a backdrop for an important future cross-disciplinary dialogue concerning designing ML-empowered tools to support the truck HMI design process. This study has provided insights into the use of ML in design work within the specific context of truck HMI design. We acknowledge the limitations of our study. The participant pool was limited and consisted of male participants, not by design but by availability of participants. Although the interview results indicated thematic saturation (Guest *et al.*, 2020), a larger sample may have introduced more diversity into the findings. This study is purposefully situated in the traditions and organizational structure of one company to allow a deep investigation of a single context instead of the production of more abstract yet more generalized principles. Applying the study's design implications in other contexts will therefore require further work to examine the particularities of other contexts. Moving forward, co-design activities with industrial practitioners in truck HMI design from algorithmic creation to concept design can further tailor ML applications to specific industry needs. Moreover, future research could explore how to conceptualize ML explainability and human autonomy and how these concepts influence human-ML team performance in the context of truck HMI design. There is a need for a social-technical perspective on ML adoption, including data infrastructure, ML-integrated organizational workflow, and the maintenance of ML.

## 6. Conclusion

Data use is fundamental in truck HMI systems design, and ML is reshaping its impact. This paper presents current data use practices and future ML use expectations of eight experts in truck HMI system design. Findings indicate that current data use practices are informed by hardware-centricity and decentralized, context-specific tasks that prioritize human expertise and cast data as support material. ML expectations center on reactive uses such as evaluation tasks, information on user behavioral patterns in the wild, and decision support, necessitating transparent and explainable ML technologies that are context-dependent on the existing work dynamics and practices of the truck HMI design process.



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Future work needs to encompass diverse and broader perspectives, including exploring proactive use of data through ML, and a closer look into necessary knowledge for Human-ML design collaboration. As we advance the capabilities of ML, it is fundamental to consider the social context of the application domain to effectively empower humans with relevant capabilities that boost the design process of commercial mobility technologies.

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