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Coordinator	*University of Skövde*
Project Manager	*Yacine Atif (yacine.atif@his.se)*
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Summary

Recognizing driver behaviors dynamically in safety modeling is a challenging problem since it involves various feature parameters about the driver, the car and the ambient traffic. The goal is to cateogrize driver behaviours into a standard metric that can be used to score safety contexts. In this project, we adopt a broad definition of context that abstracts multimodal data into aggregated driving behaviours (Biondi, Strayer, Rossi, Gastaldi, & Mulatti, 2017). Raw data span the driver and the vehicle dimensions, to formulate multiple levels of context abstraction that reveal higher level and decision-leading features.

Raw data used to detect driver distraction employ onboard cameras and other physiological sensors (Nees, 2021). Our project partner houses some levels of these solutions that we investigated and proposed to optimize further. Along the vehicle dimension, raw data sources is expanded with CAN bus data, such as Lidar and GPS data, which can be fused in different ways to infer driving feature conditions, such as speed, acceleration, lane keeping or changing instances, as well as car-following gaps. In doing so, driver state features that are inherent to individual drivers' physiological attributes are consolidated. Data fusion processes incorporate vehicle information, such as lane deviation and steering wheel motion to better diagnose driving contexts that are used to estimate risk levels. Further integration can involve ambient traffic modality such as the volume of ambient vehicles, as well as other sources of distraction such as cognitive distraction. However, these latter considerations are outside the scope of this project.

We introduce the concept of driving analytics that employs data-evidenced and AI-grounded methodologies to optimize the precision of context detection, used to assert risk levels. On- board sensors, such as eye-tracking cameras analyze driver's visual distraction, through extracting features based on some image analysis processes. The application of some machine learning techniques categorizes driver states into distraction patterns. Similarly, we proposed to integrate vehicle indicators to recognize driving patterns. Subsequently, driver state and vehicle dynamics are fusionned to obtain a higher-precision risk indicator, used by ADAS software to monitor and assist drivers.

This project presents a proof-of-concept to characterize contexts using a multimodal perspective of data. In doing so, we report and categorize the extensive state-of-the-art works related to driver modeling (Hermannstädter & Yang, 2013), and we outline the scope of a follow-up larger-scale project, which proposal has already been drafted and submitted.

Multimodal Data for Road User Behavior Analysis to Support Safe Driving Patterns

1. Background

Future transportation landascape will include a mix of driving-assisted vehicles, with varying degree of automation levels and driving assistance technologies. Human-operated vehicles with Advanced Driver-Assistance Systems (or ADAS) are projected to prevent human-failures at the wheels. Driver state factors and their evolution such as fatigue, inattention, or drowsiness. These two factors combined shape the level of distraction of drivers (Regan & Young, 2008).

ADAS is expected to instill safety and trust to support a safer transition into autonomous driving. By analyzing factors that contribute to bridge the gap between humans and Autonomous Vehicles (AVs), current drivers are made aware of unsafe driving, whereas future passengers need to build trust in autonomous decision-making measures by their vehicles. Indeed, as illustrated in Figure 1, In the meantime, safety holes need to be accounted for and prevented, as part of Sweden's Vision Zero strategy for safe transportation.

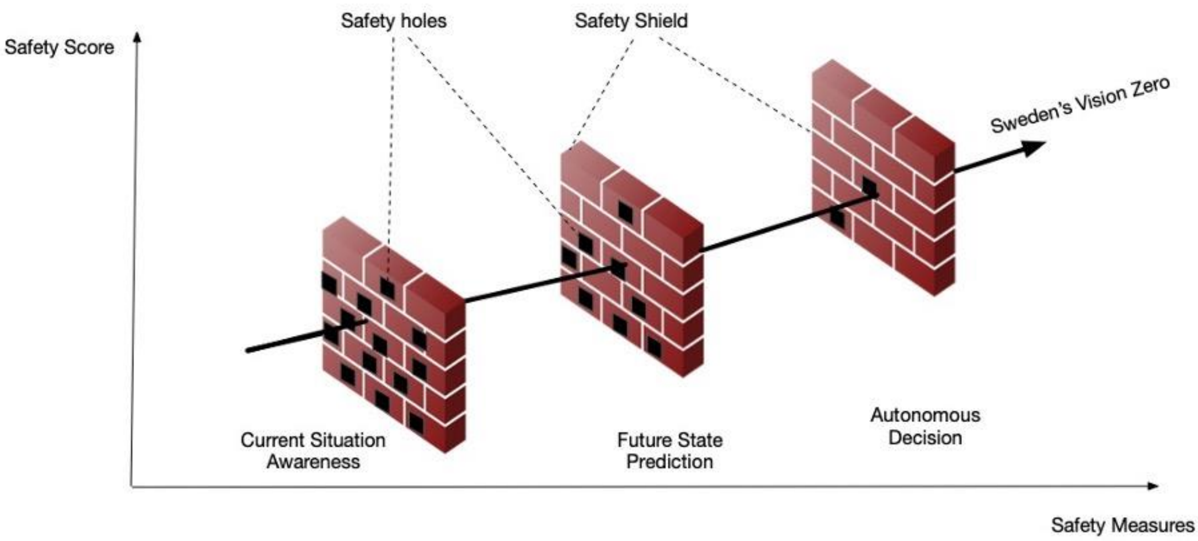

Figure 1. Safety Evolution

Safety gaps are exposed by a lack of awareness in current context and future state prediction. This safety deficiency can be overcome with active safety measures to likely

collisions (Khan and Khusro 2020). Nissan labels the collection of these high-tech safety measures as Safety Shield. These safety measures are provided by enhanced Advanced Driving Safety Systems (Nees 2021), which quantify a safety score used to adjust the provided safety measures. Future ADAS are increasingly enabled with cognitive prediction capabilities in order to forecast unsafe conditions and correct driver intentions. However, care must be taken to ensure the driver is provided with the appropriate amount of information to make effective decisions

Visual distraction is a prominent contributing factor to unsafe driving, inducing levels of inattention to critical driving activities (Regan & Young, 2008) (Hermannstädter & Yang, 2013). However, several studies propose to consolidate the outcomes of visual distraction indicators with vehicle dynamics data as suggested in Figure 2 (Jain & Busso, 2011) (Sathyanarayana, Boyraz, Purohit, Lubag, & Hansen, 2010).

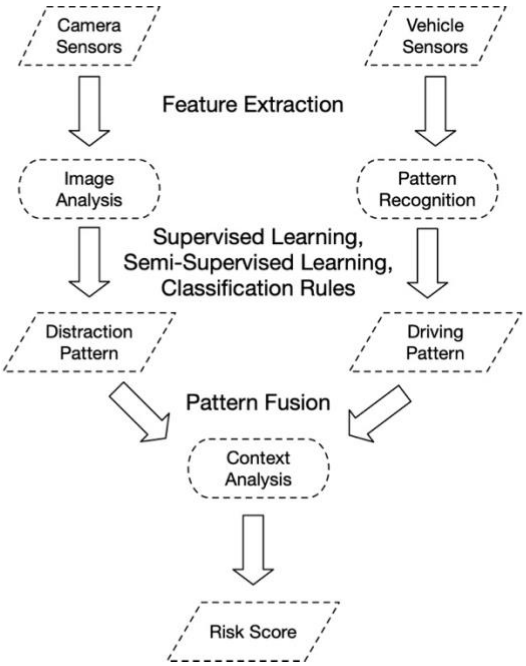

Figure 2. Multimodal Pattern Analysis for safety score computation

The fusion of driver physiological data and vehicle dynamics data is expected to increase the precision of safety score computation. However, this approach faces several challenges which are outlined next.

- How to identify context from the data at hand?
- How does context variation relate to driving behaviour?
- How is ADAS made aware of context variations?

The resolution of these challenges answer actual industrial needs to formulate accurate safety scores. Besides active safety, these scores are instrumented to induce transparency in driving activities and incentives to safe driving practices. This is precisely what Tesla is aiming at, by adding safety score functionalities lately to their cars[1]. Yet, this recent addition is still Beta which indicates that further research is both needed and expected to formulate a more accurate safety score approach. We expect other car manufacturers to follow this trend and hence use the outcomes of this research.

2. Project set up

2.3 Purpose

The importance of this project is illustrated by its contribution to advance the state-of-the-art and commercial solutions that pave the way to embrace trust into driverless vehicular systems. These forthcoming advances and solutions include safety score formulation (Arbabzadeh & Jafari, 2018), context identification (Al-Sultan, Al-Bayatti, & Zedan, 2013), driver modeling, explanation and visualization of driving performance, data services provisioning, and building trust in driving assistance systems.

The purpose of this project was to explore machine learning techniques used to analyse driving patterns that could lead to the discovery and correction of unsafe driving behaviors. The goal was to justify the correlation of multiple data sources made available today by car manufacturer technologies to support data-driven driving safety. We wanted to map driving behaviors to driving context variations to identify risk factors used both to anticipate hazardous situations and aggregate to educate drivers.

The outcome of this project was expected to form the basis for a larger funding application and support the development of realistic driving simulators under a range of safety scenarios. Indeed, existing simulators focus on traffic and driver body configurations. Little research investigates the integration of cognitive attributes into such simulators. The goal was to enable future cognitive ADAS as a milestone towards autonomous driving, by learning best driving and meet personalized safe driving features.

2.4 Objectives

Quoting the initial application, the objectives were: “the project capitalizes on existing distributed and multidisciplinary sensing platforms to enrich road transportation systems with new sources of information… The project aims at planning a transportation data platform to support new, modern applications for driving data analysis.” Later through the application, we also stated that” various sources of

[1] https://www.tesla.com/support/safety-score

transportation data remain unexploited, and which correlations could reveal new innovations... The data platform derives insightful patterns that impact driving safety. ”

It is clear from the previously stated objectives above, that the aim was to delve into accounting for data sources that support driver-centered safety. Then, we wanted to develop some form of aggregation that conveys meaningful safety information. That is precisely what we contributed throughout our investigation by introducing a new concept “driving analytics”, whereby the context provides an account of relevant safety data sources, and safety score provides the sought form of data aggregation.

2.5 Project period

The project spanned the period from 2021-01-01 to 2021-09-30. This period was divided into three work phases. First, we had to enrich the background by analyzing the literature for data-driven safety use cases. Next, we analyzed the data at hand used by our partner company to detect driver distraction and inattention. Finally, we develop a methodology for data aggregation, based on contemporary machine learning techniques.

2.6 Partners

We worked in close collaboration with Henrik Lind from SmartEye AB, who contributed regular feedback and guidance throughout the project. SmartEye AB instrumented vehicles with commercial solutions that integrate video cameras, an automatic eye tracker and GPS receivers (Kircher, Kircher, & Claezon, 2009). They also utilize CAN bus data to log vehicle dynamics (Jain & Busso, 2011). The goal was to detect driver drowsiness and inattention instances through baseline data collection. Subsequent warnings are activated accordingly like seat vibration, when such instances were detected, in real-time (Bergasa, Nuevo, Sotelo, & Vazquez, 2004).

3. Method and activities

The advocated methods that we used are illustrated in Figure 3, which introduce our proposed “driving analytics” scope of research. The process works in tandem by applying contemporary analytics techniques to driving data, to diagnose context. The first method in this driving analytics lifecycle is “Descriptive Analytics” which includes a set of activities used to reveal what has happened in the past. These activities include identifying influential data that contribute to context diagnosis, as well as assessing data availability and accessibility.

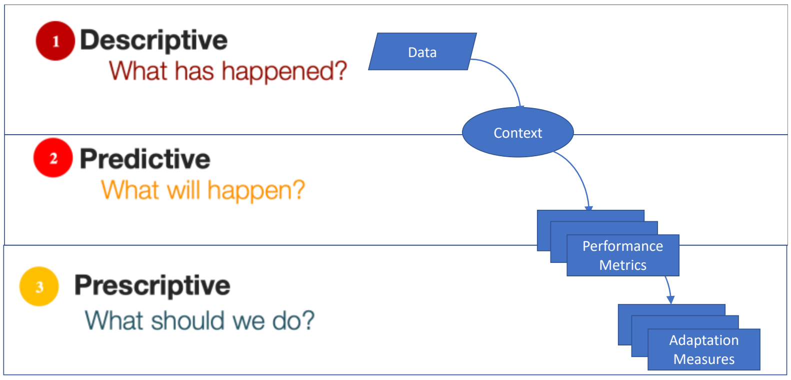

Figure 3. Driving Analytics

The level of sophistication in the scientific approach to descriptive analytics ranged from observing data transformation along some safety KPIs to identifying variables of interest. Subsequently, machine learning techniques are investigated to discover correlations between variables, revealing relationship patterns between the values of variables. Or even extending the analysis into cause-effects to establish the causes or factors that affect safe driving.

Predictive analytics answers the question what is likely to happen in the future. The process also involves machine learning models based on past experiences and the current context data retrieved from the descriptive analytics phase, to pinpoint the high-risk areas. The accuracy of some performance metrics used to evaluate unsafe trends is the end goal of a predictive analytics model. However, we observed that increasing accuracy levels come at a high computational cost, which could be prohibitive for on-the-fly decision-making in smart-mobility environments. Hence, I engaged a final year thesis project in Computer Science, where students under my supervision investigated parallel architectural platforms for running machine learning algorithms (Roderus et al. 2021). This is consistent with contemporary ADAS platforms, for which computer companies are designing dedicated infrastructures[2].

Once the future unsafe state is demystified, prescriptive analytics answers the question "what should we do to adapt to the foreseeable risk? The adaptation measures may induce situational changes that are feedback to descriptive and predictive algorithms, stating a new driving analytics iteration, that keeps continuously vehicles within safe driving boundaries.

4. Results and Deliverables

The main outcome of this research is a context-aware and intention-aware approach safety score approach that correlates driver-error in knowledge, performance, and

[2] "Dell EMC Isilon: Deep Learning Infrastructure for Autonomous Driving", NVIDIA Drive Hardware,

intent. Context corroborating to driver error is derived from descriptive analytics of driver state and driving behaviour factors, whereas driver intentions use predictive analytics to categorise intended manoeuvres.

Outcome 1: Safety Score Model

The first outcome of this project is a safety score model illustrated in Figure 4, used to guide assistive measures that reduce human-error margins, accordingly, as part of prescriptive analytics activities. This model suggests the combination of context and intended maneuver to score driving safety in a way that is sensitive to the present driving situation and future driver intention. Hence, we first, we need to characterize context, quantitatively, and then, we also need to predict the next maneuver intended by the driver. The exact formulation of the safety score function is part of a follow-up project proposal- However, as part of this project we looked into answering the sub-questions 2 and 3 shown in Figure 4.

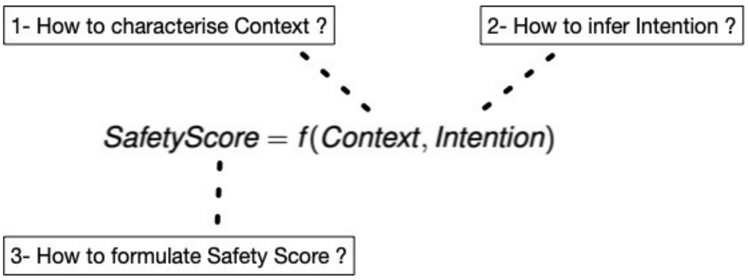

Figure 4. Safety Score Model

Outcome 2: Context Characterization

This outcome supports the design of context aware ADAS by supplying an additional context identification layer. The accuracy of this context raises trust in the provided assistive interfaces that car manufacturers develop to alleviate unsafe driving situations (Khan & Khusro, 2020). We propose a driver classification algorithm, which classifies drivers using behavioural measures as illustrated in Figure 5.

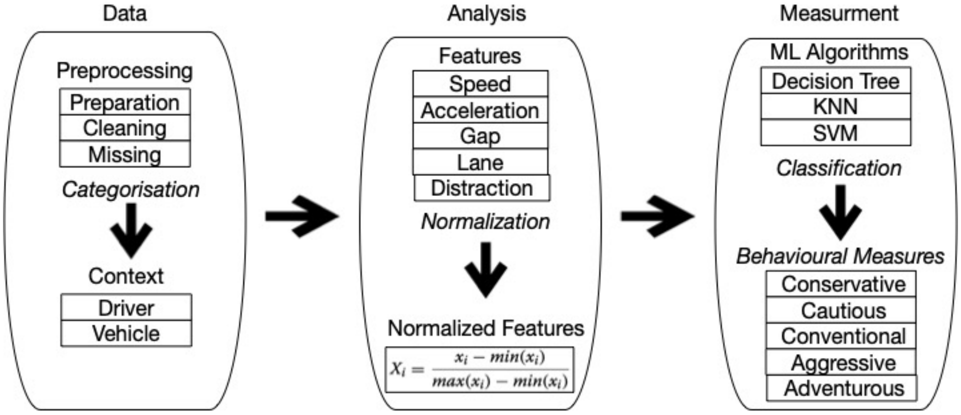

Figure 5. Context Characterization Model

The process starts by a pre-processing step to delete redundant data and infer missing ones using learning algorithms like KNN (K-Nearest Neighbours) {Karri, 2021}. Then data is categorized along driver and vehicle context dimensions. Next, we select representative features used to discover behavioral patterns. These features instrument vehicle dynamics and distraction data. Vehicle dynamics include speed, acceleration, car/following gaps, and lane change frequency. Distraction is the driver dimension of context that evaluates driver physiological data such as eye gaze and inattention instances to the driving task. These two- dimensional (vehicle and driver data) and their multimodal feature values may be further transformed as they have different scales, through some normalization process prior to their use by machine learning algorithms in the next phase of context characterization.

The context characterization model employs machine learning algorithms to classify the resulting feature values into behavioral measures, which are used to index the context data captured from the start of this analysis process (Moosavi, Omidvar-Tehrani, Craig, Nandi, & Ramnath, 2017). A deep-learning network is illustrated in Figure 6, that infers behavioral class indexes. In addition, the class-wise centroid distance is used as the context offset to derive a decimal quantification of context.

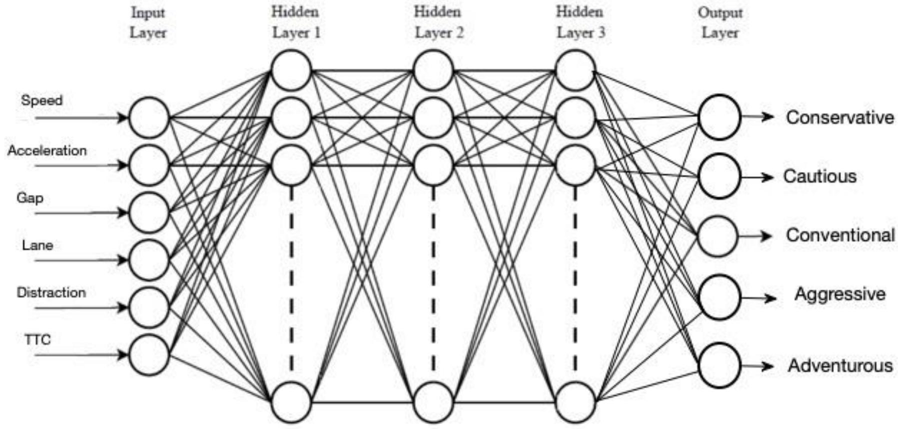

Figure 6. Context characterization based on behavioral measures

Outcome 3: Driver Intention Prediction

Although beyond the scope of the pre-study scope anticipated in the application proposal, our proposed safety score formulation drove our investigation to investigate driver intention. As illustrated in

Figure 7. Because of our limited highway scope, the possible intentions are also limited to lane changing related maneuvers. A possible approach to intention prediction employs Hidden Markov Model (HMM), which we investigated to predict intended maneuvers (Tran, Sheng, Liu, & Liu, 2015).

Given observed features such as vehicle dynamics context, HMM discovers a sequence of hidden states that reflect future intentions.

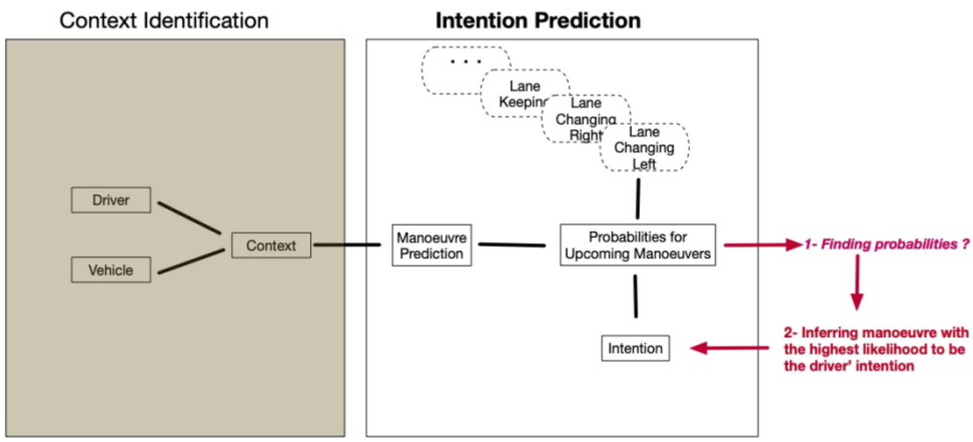

Figure 7. Driver intention prediction

Observed features that can be used are the vehicle steering, velocity, and yaw as illustrated in Figure 8. Following a training phase that use data collected from the vehicle dynamics context in the context characterization phase, the prediction model infers transition probabilities. Given a trained HMM model and a set of driving dynamics features, the manœuvre with maximum probability is inferred as the predicted intention.

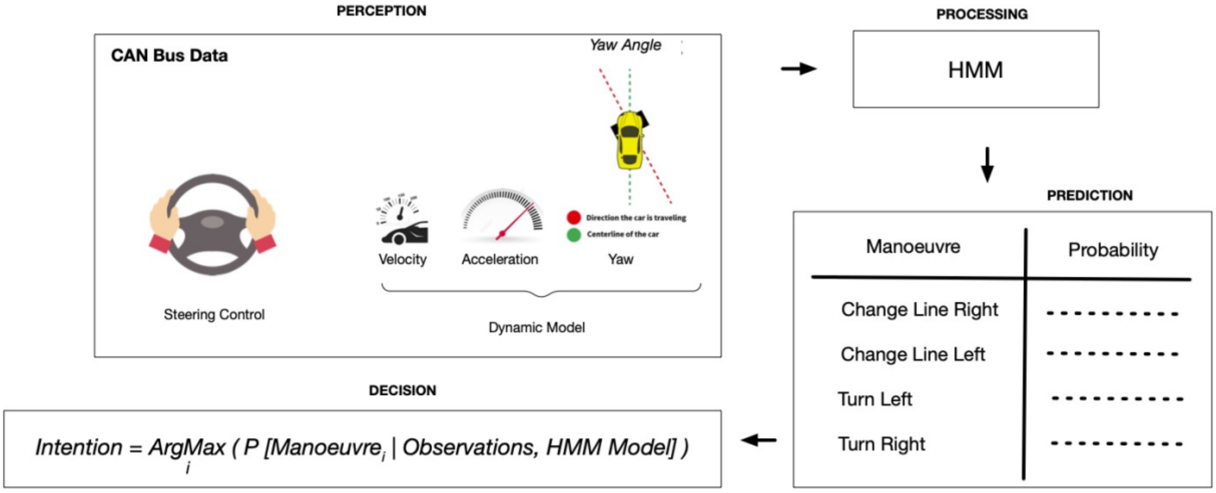

Figure 8. Intention prediction process

5. Conclusions, Lessons Learnt and Next Steps

Our pre-study resulted in a pertinent follow-up project that includes an evaluation of context-aware driving safety models, that were investigated and elaborated throughout the pre-study phase. Our definition of context incorporates both driver distraction and vehicle dynamics data. We also integrated an approach to predict intention based on HMM model. Both driving context and driver intention are suggested to contribute to the safety score formulation used both for active safety and aggregated across time periods to instil driving transparency. The aggregated safety can also be used as incentive for safety, like Tesla did turn safety into a competition game as drivers share their score in a leader-board.

We already drafted a follow-up project that builds on the pre-study to experiment the proposed solutions and support the industry with sophisticated active and aggregated safety indicators. A sketch of the follow-up project is illustrated in Figure 9, that incorporates a team from University of Skövde and University of Jonköping, as well as a list of industry partners.

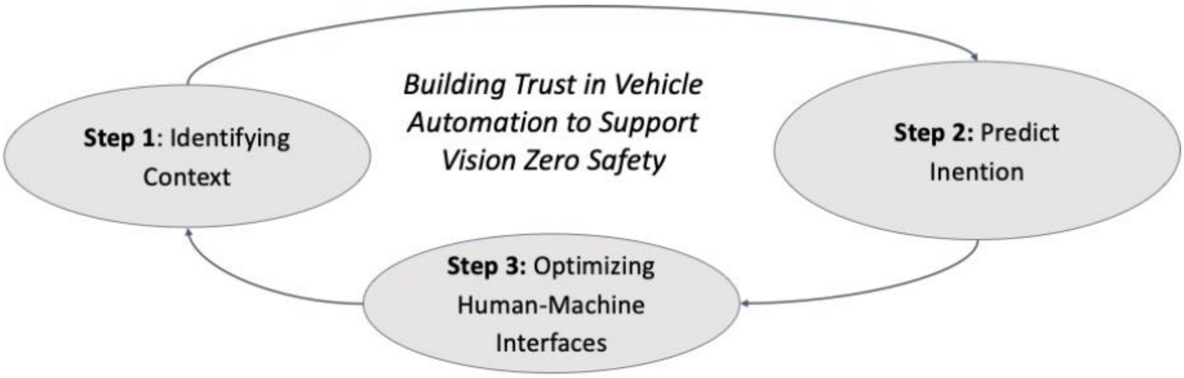

Figure 9. Follow-up project

6. Dissemination and Publications

I have been sharing my progress and findings on the go with Safer community. I delivered five pre-study related seminars since the approval of the project proposal to update the community about the latest additions to my investigations. These seminars occurred as outlined below, and were meant also to stimulate research and networking opportunities in the project scope related areas:

1. November 02, 2020: Y. Atif, "Detection and Classification of Driver State and Driving Patterns", AI Brokerage Event, Safer.

2. November 02, 2020: Y. Atif, "Multimodal Data for Road User Behavior Analysis to Support Safe Driving Patterns, Pre-Study Introduction.

3. January 21, 2021: Y. Atif, "Detection and Determining context: Integrating Data to Support Safe Driving Patterns", AI Brokerage Event, Safer

4. April 21, 2021: Y. Atif, "Context-Aware Driver Distraction Analysis to Reduce Driving Error", Pre-Study Update, Safer.

5. October 28, 2021: Y. Atif, "Multimodal Data for Road User Behaviour Analysis to Support Safe Driving Patterns", Pre-Study Results, Safer.

Besides these the above dissemination forums, there were also several side meetings with industry representatives where the pre-study outcomes were presented in view of building a consortium for the follow-up project. This pre-study stimulated effort has ultimately led to the elaboration of a draft grant proposal that is expected to be submitted to Knowledge Foundation (KKS). A publication is being drafted, which shares with the wider research community the outcomes of this project following the sections outlined in this report. The current state of the publication includes the motivation, the problem description, the background, and the methodology sections that were briefly summarized in this report. An experimental evaluation section is expected to be added.

7. Acknowledgement

I would like to thank Safer for extending this funding opportunity that helped trigging a wider interest among colleagues here in University of Skövde as well as colleagues currently positioned at Jonköping University. Together, we drafted a larger project proposal that is being considered for KKS submission, following the work outcomes stimulated by this pre-Safer-funded study.

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