UDRIVE

European Naturalistic Driving Study

Feasibility of commercial applications

Deliverable 54.1

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Executive Summary

This UDRIVE deliverable addresses different ways in which Naturalistic Driving (ND) data can be used for development of driver support functions and driver coaching as well as to develop a business model for continued and open access to UDRIVE data after the project.

How can ND data can be used by the vehicle manufacturing industry to facilitate the development of driver support functions ?

For function development (ranging from passive to more advanced driver-assistance systems (ADAS) as well as higher level of automation functions), capturing both normal driving as well as accidents and incidents through collected naturalistic driving data (NDD) can be used in combination with statistical crash data. Examples of where function developers can have a strong need for naturalistic driving data is e.g. for basic tuning of the automated driving functions. NDD can be used in order to *define target scenarios* and to *select appropriate countermeasures* as well as *for sketching use cases* in early development phases. Information captured in NDD can serve as input when *developing proper driver-, system-, vehicle- and environmental models* for pre-crash and crash simulations and when *evaluating the safety performance of a specific driver support function.*

Further more, chapter two described simulation tools that could benefit for virtual testing. For example, to assess the benefits of an ADAS it's necessary to know how drivers behave in specific situations and how drivers react to the interventions by their vehicle. ND data (with or without systems) can be used to provide the relevant data to develop, test and validate the behaviour models. PEARS network and OPENPASS are initiatives that harmonise simulation tools and create a new software framework for simulation and evaluation of active safety and different types of automated functions in an integrated manner.

How can ND data be used in behaviour-based safety programmes?

In order to shape custom-made behaviour-based driver coaching, in-depth behavioural knowledge is required. A major part of this in-depth knowledge is to comprehend the mechanisms of driver behaviour. One example of the reason why it is necessary to comprehend specific behaviour is to successfully avoid a precipitating event, in other words understand behaviour in safety critical events that *do not* lead to a crash event . Thus far, the results retrieved from the analysis of the short time-span before a precipitating event has been often used for understanding crash causation and less for tailormade driver coaching and training. Two specific use cases showing the value of ND data for enhancing coaching strategies for driver coaching programmes are coaching teen drivers and coaching commercial truck drivers. Driver coaching can be aimed at safety, fuel consumption, vehicle care, driver health, customer communication, stress management and other driving behaviours. For successful safety programs and coaching programs, it is necessary to track reliable ND data to provide timely and effective feedback to the driver. The intended results of coaching programs are the formation of new habits. If successful, this can be accompanied by a change in attitude, feelings, stress level, and self-perceived performance on the coaching targets.

What is the view of the industry and research centres on the re-use of ND data?

A questionnaire was distributed in order to get input from the industry and research centres on how they value and use ND data. Nineteen responses were gathered, some of which were followed up by phone conversations. Additional phone conversations took place in order to complete the industry representativeness of the sample.

There was a highest interest expressed for in-vehicle data from CAN, radar and cameras (outside and driver views). There is a growing interest to access (historic) probe data, which is considered to be highly valuable to understand traffic bottlenecks or mobility patterns. The potential is perceived by the parties but they see so many legal and practical hurdles to access such data that it easily gives up along the way. A recurrent issue mentioned by the potential ND data users is their lack of expertise to analyse the data. The community

at large would welcome any improvements to access collected ND data but the lack of expertise seems to remain the greatest issue.

For the ones who have ND data analysis expertise, their main plea is to have a one-stop European approach where many different data sets can be shared with economies of scale on the data infrastructure and required computing power. If a data infrastructure would exist, a give and take model seemed to be the most likely: the parties expressed their interest to share data at the condition that they can access other data sets. On the willingness to pay, most of the respondent could not express themselves at this stage; 50% remained positive to pay for the access to the data whereas a third preferred an option where they participate commonly to the cost guaranteeing the access to the data. Still, the impression during interviews was that the majority preferred the option of paying for what they ask for rather than having to develop all skills to analyse the data.

What are the possibilities for continued and open access to UDRIVE data after the project?

Main challenges are: 1) the costs to host the data and keep it available 2) financial model for continued access, and 3) privacy barriers (video data of faces etc.). FOT-Net Data project has described a series of six financial models for the re-use of FOT and ND collected data by interested parties. Two different financial models were proposed for UDRIVE: (i) a member-based model in which first UDRIVE partners become members and additionally third parties can become members and (ii) a project-based model that aims at possible coverage from external projects of the costs. Each project within has to pay the same amount for the access of the data. The ND data can be mined remotely using authorised access. This solves the privacy issue: the group of organisations keeps full control on the privately sensitive data through strict data protection procedures. At the same time it can still access private data for any research studies ordered by a customer. However, this solution only solves the problem of the UDRIVE ND data collected during the project, which brings the question of the business model for collecting more data in the future.

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1 Introduction

UDRIVE is the first large-scale European Naturalistic Driving Study on cars, trucks and powered-two wheelers. Road transport is indispensable for the exchange of goods and persons. However, it has severe negative consequences, among others related to road safety and the environment. In order to meet EU targets, both the number of crashes and vehicle emission levels need to be reduced substantially. Therefore, in order to identify the next generation of measures that will enable us to improve road safety up to the Horizon 2020 and beyond as well as the necessary approaches to make road traffic more sustainable, a far more in-depth understanding of actual road user behaviour is needed. The UDRIVE project contributes to developing this in-depth knowledge by conducting the first large-scale European Naturalistic Driving Study.

This deliverable describes the results of the work carried out in WP54, which is part of SP5: Impact of UDRIVE. The deliverable will address different ways in which Naturalistic Driving (ND) data can be used for development of driver support functions and driver coaching. Two main areas will be addressed:

- How ND data can be used by the vehicle manufacturing industry to facilitate the development of driver support functions (chapter 2);
- How ND data can be used to provide driving performance feedback in the context of behaviour-based safety/fuel efficiency programmes in commercial fleets. (chapter 3).

Results of a stakeholder questionnaire and possible business models for ND data are investigated (chapter 4). Finally possible options for continued and open access of UDRIVE ND data are described (chapter 5).

2 Use of ND data in driver support function development

Regardless of technical domain, where functions are being developed which should interact with a human in one way of another, it is crucial to have explicit understanding of real problems or issues experienced by users in real environments, that is, have a user centred design process (ISO 9241-210). Naturally, real world data is necessary in order to create this understanding as well as when creating accurate functional requirements and specifications towards function development.

For function development (ranging from passive to more advanced driver-assistance systems (ADAS) as well as higher level of automation functions), capturing both normal driving as well as accidents and incidents through collected naturalistic driving data (NDD) can be used in combination with statistical crash data (e.g. from national crash databases such as the Swedish traffic accident data acquisition database STRADA (2017) or CARE (2017) which gather accident data from across the EU Member States into one central database. In addition to the national high level crash databases, more in-depth crash data e.g. from on-site investigations can be used (e.g. GIDAS, 2017) well as more quasi- or controlled experimental data conducted in simulators, in field, on test tracks as well as in crash laboratories. These sets of data can be used in order to identify critical situations, accidents or collisions, for which the support function or other countermeasures could provide a solution. Accident databases, for example, are studied to determine, which accidents occur most frequently, what are the main causes, and what is the resulting impact regarding numbers of fatalities or levels of injuries due to those accidents. To provide data to such databases, accidents that occurred on the road are studied by either the police or dedicated accident analysis teams. Data are analysed and stored (often on national level), to provide an overview of typical accidents with their contributing factors and the frequency of occurrence. These data are used by researchers and engineers to build up knowledge on typical critical situations that might result in an accident, primarily to design solutions through which such accidents are prevented in the future. However, the data collected quite often provides information on the type of accidents (e.g. right turn, rear collision, etc.) and whether other road users were involved, but not necessarily so much on the different factors leading to the accident. Other data sets and especially data of Naturalistic Driving Data (NDD) can provide more insight in these contributing factors.

Naturalistic Driving Data (NDD) can be classified as either Naturalistic Field Operational Tests (NFOTs) or naturalistic driving studies (NDS) (Bärgman, 2015). According to the classification provided by Bärgman, the NFOTs evaluate some form of safety countermeasure and normally include both treatment and baseline conditions in order to conduct statistical comparisons, for example, with and without the introduction of a specific driver support function. As a comparison, NDS does not include experimental conditions such as baseline and treatment periods, but instead consist of pure data collection in order to understand specific traffic situations and associated driver behaviour etc (ibid). With NDS data it is more challenging to clearly state causality (e.g. whether a specific factor has an influence on the causation of incidents and accidents). Since NFOT normally include a baseline period this period could be considered being a sort of NDS if drivers are indeed free to drive “in a normal way” without influence of further experimental conditions.

NDS data sets such as UDRIVE , 100 car study (Dingus et al., 2006), SHRP2 (Boyle et al., 2012), ANDS (ANDS) as well as NFOT data sets such as EuroFOT (Kessler et al., 2012), DRIVE C2X (Schulze et al., 2014), IVBSS (Sayer et al., 2011) consist of continuously logged data from, for example, accelerometers, GPS, cameras (on-road, towards driver), radars etc. Continuous naturalistic driving data has been used, for example, the identification of the main causes leading to accidents as done in the 100 car study (Neale et al., 2005) as well as more detailed analysis of crash risks associated with secondary tasks (prevalence and relative risk) in the SHRP2 data set (Victor et al., 2014). Event based naturalistic driving data has been used, for example, reconstructing vehicles’ trajectory (Kusano et al., 2013), evaluation of collision avoidance algorithms (McLaughlin et al., 2008), identification of driving style/patterns (Simons-Morton et al., 2013) and evaluation of injury causation mechanisms (Andersson et al., 2010). Naturalistic driving data can also be collected by event triggered recording systems, which collect safety critical events based on different kinematic triggers. The recorded events can contain video data on the road ahead and on the driver, see e.g. SmartDrive Systems (SmartDrive, 2017) and Lytx (see Figure 1 for a screen shot of the event viewer including so called crash behaviours and action plan for coaching), the maker of DriveCam (Lytx, 2017) or be more traditional event data recorders (EDR), which exist in most modern vehicles, where video is generally not included. For the latter, pre-crash speed, engine throttle, brake use, information on airbag deployment, etc. are examples of logged variables.

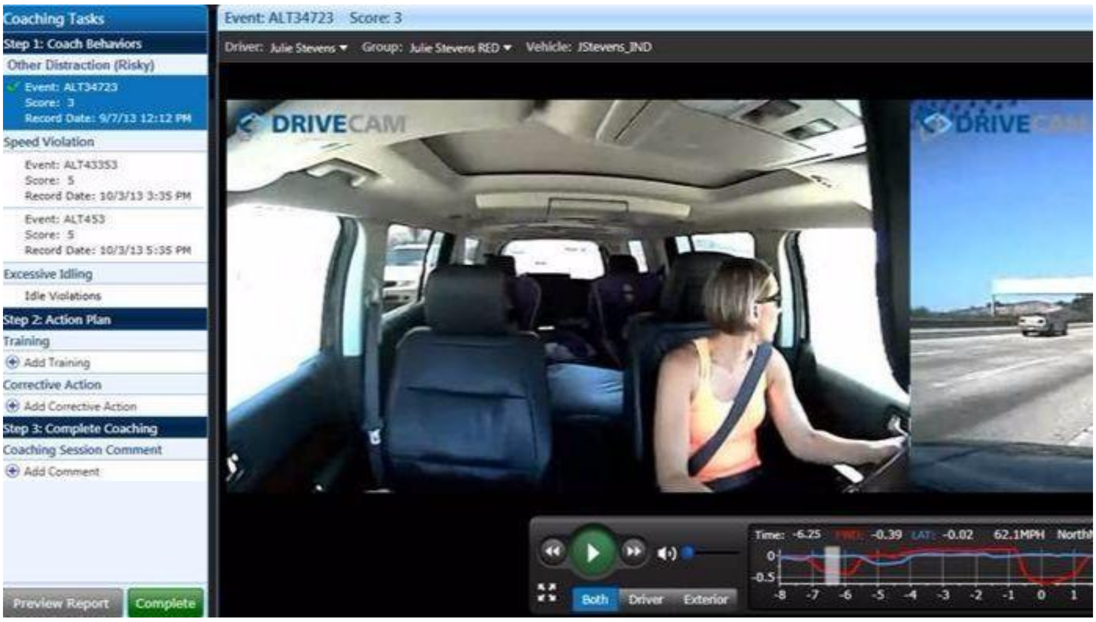


Figure 1 Lytx's DriveCam system (Lytx, 2017)

Examples of where function developers can have a strong need for naturalistic driving data can be e.g. to quantify the variety in driver preferences for different driving parameters (mean value and distribution). Such information is essential for basic tuning of the automated driving functions (e.g. finding the most suitable acceleration/deceleration values, time headway, speed profile in general, and even in the position of the car within the lane). It can also be of importance to understand the response of drivers while experiencing critical situations (e.g. studying possible delay in response and subsequent driver action), in order to perform the best possible support actions in line with the common driver behaviour. The system response and driver response to a critical situation should ideally act in a compatible way. Moreover, some functions might need input about the state of the driver, to determine whether or not a transition of control is required. For higher levels of automation, the human might not be a part of all aspects of the driving task. However, NDD can still be used as a data source to feed and train machine learning algorithms. Following this, not only critical situations should be collected, but all type of situations, also those of normal driving. Depending on the chosen development strategy, there is more or less interest in the specific behaviour of the driver in all situations. NDD be used for assessment of behaviour of the behaviour of the ego vehicle and its driver but also other road users in relation to ego vehicle. Frameworks on NDD use in function development

Structured frameworks for how to use NDD as part of function development (e.g. driver support functions) has been developed; see e.g., EFrame for commercial vehicles; Engström & Wege, 2016). The safety analysis framework in EFrame is intended to be used to (i) identify and focus on the most important safety problems, (ii) estimate the potential and actual safety benefits of safety systems and services and (ii) identify the data sources needed to perform these analyses. NDD is one source of information to be used. For an overview of the different data sources linked to the higher objectives in EFrame (Figure 2).

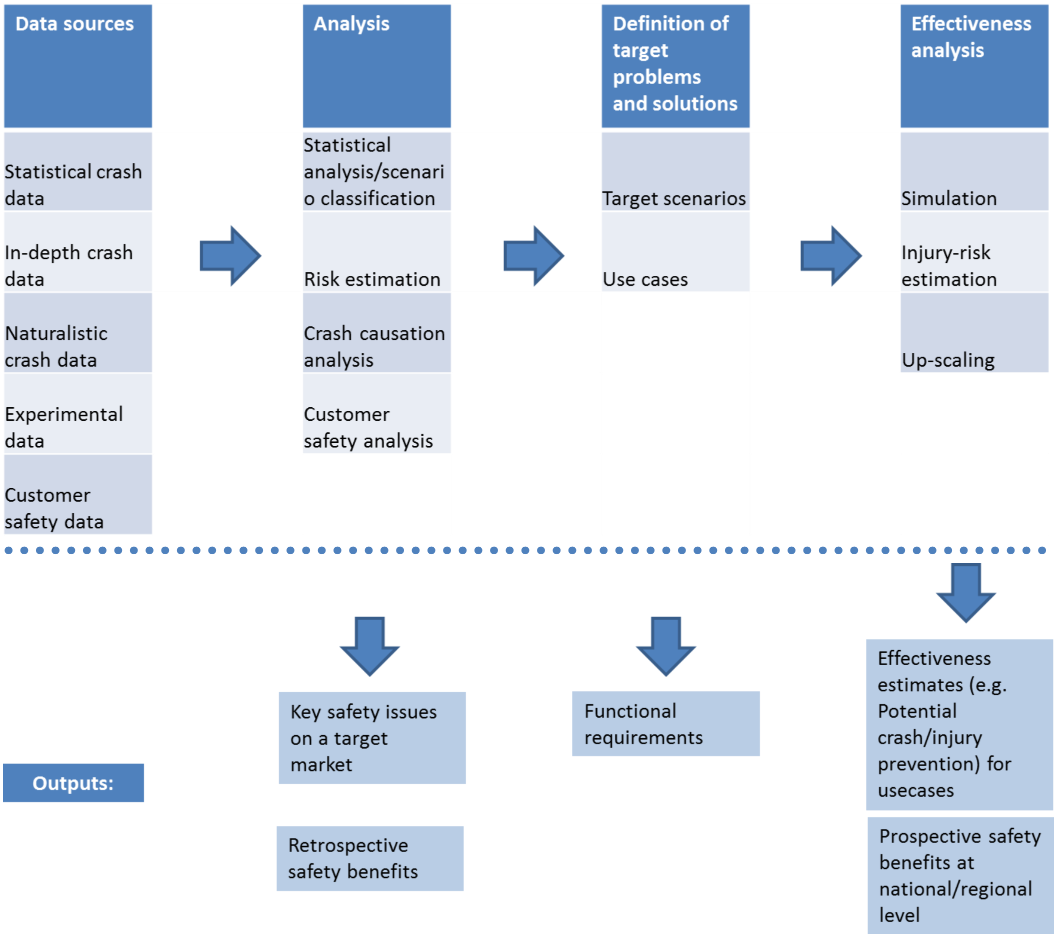
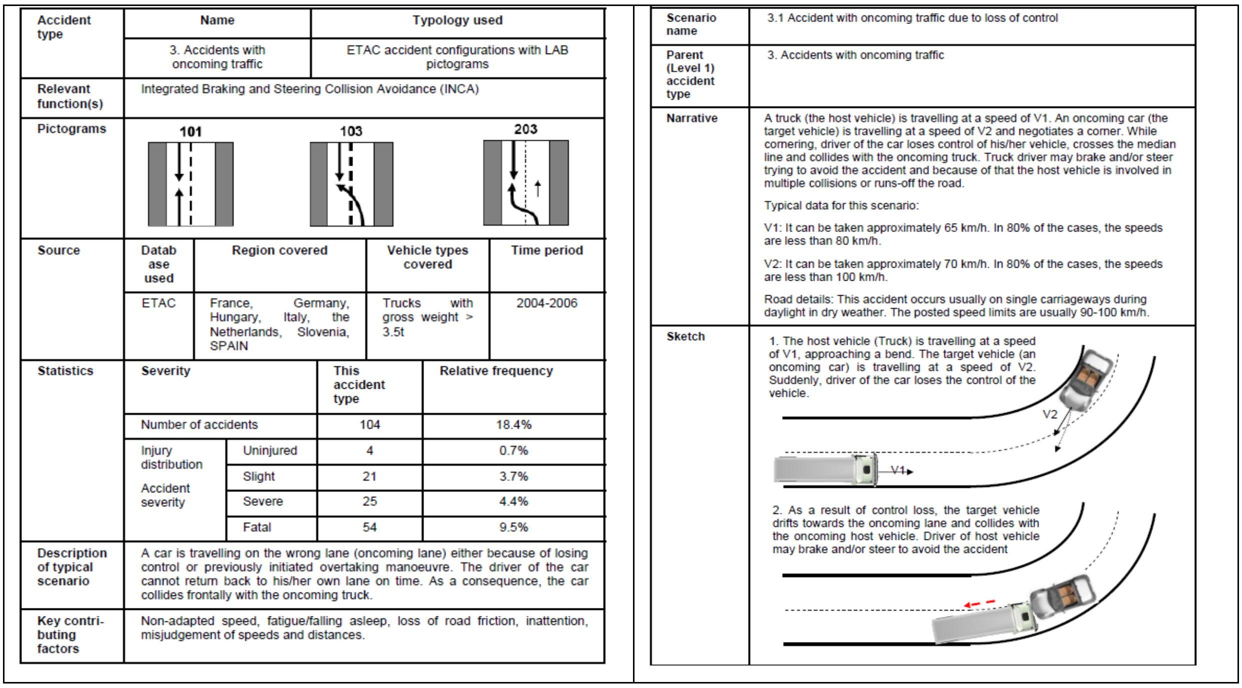


Figure 2 Overview of the 'Evaluation Framework for Commercial Vehicle Systems and Services' from the EFrame project (Engström & Wege, 2016).

As described above as well as in the EFrame project (Engström & Wege, 2016), NDD containing in-depth information about crashes can serve as an important input throughout the development process complementing, what can be extracted from other data sources.

NDD can be used in order to *define target scenarios*, that is, accidents and other undesirable outcomes. Tivesten (2012, 2014) provides insight in how to use different sources of real world data such as crash mail survey, insurance claims, and naturalistic driving data in order to *prioritize crash types*, study *contributing factors*, and to *select appropriate countermeasures*. In the interactIVe project target scenarios were defined based on crash statistics from national and in-depth crash databases (see Figure 3 for an example; Mäkinen, et al. 2010; Hesse, et al., 2011) while Gordon et al. (2010) in the ACAT programme combined NFOT with national crash data focusing on road departure crashes. Bianchi Piccinini, et al. (submitted) analysed crashes and near-crashes involving commercial vehicles in China captured by event triggered recording system, where the results can serve as input when identifying main conflict scenarios and factors contributing to the events.



Accident type	Name	Typology used		
	3. Accidents with oncoming traffic	ETAC accident configurations with LAB pictograms		
Relevant function(s)	Integrated Braking and Steering Collision Avoidance (INCA)			
Pictograms	101	103	203	
Source	Datab ase used	Region covered	Vehicle types covered	Time period
	ETAC	France, Germany, Hungary, Italy, the Netherlands, Slovenia, SPAIN	Trucks with gross weight > 3.5t	2004-2006
Statistics	Severity		This accident type	Relative frequency
	Number of accidents		104	18.4%
	Injury distribution Accident severity	Uninjured	4	0.7%
		Slight	21	3.7%
		Severe	25	4.4%
		Fatal	54	9.5%
Description of typical scenario	A car is travelling on the wrong lane (oncoming lane) either because of losing control or previously initiated overtaking manoeuvre. The driver of the car cannot return back to his/her own lane on time. As a consequence, the car collides frontally with the oncoming truck.			
Key contri-buting factors	Non-adapted speed, fatigue/falling asleep, loss of road friction, inattention, misjudgement of speeds and distances.			

Scenario name	3.1 Accident with oncoming traffic due to loss of control
Parent (Level 1) accident type	3. Accidents with oncoming traffic
Narrative	A truck (the host vehicle) is travelling at a speed of V1. An oncoming car (the target vehicle) is travelling at a speed of V2 and negotiates a corner. While cornering, driver of the car loses control of his/her vehicle, crosses the median line and collides with the oncoming truck. Truck driver may brake and/or steer trying to avoid the accident and because of that the host vehicle is involved in multiple collisions or runs-off the road. Typical data for this scenario: V1: It can be taken approximately 65 km/h. In 80% of the cases, the speeds are less than 80 km/h. V2: It can be taken approximately 70 km/h. In 80% of the cases, the speeds are less than 100 km/h. Road details: This accident occurs usually on single carriageways during daylight in dry weather. The posted speed limits are usually 90-100 km/h.
Sketch	1. The host vehicle (Truck) is travelling at a speed of V1, approaching a bend. The target vehicle (an oncoming car) is travelling at a speed of V2. Suddenly, driver of the car loses the control of the vehicle. V2 V1 2. As a result of control loss, the target vehicle drifts towards the oncoming lane and collides with the oncoming host vehicle. Driver of host vehicle may brake and/or steer to avoid the accident

Figure 3 Target scenario example with accident involving on-coming traffic (Mäkinen, et al. 2010)

NDD can also be used when *sketching use cases* in early development phases (see Figure 4), that is, high level solutions describing for example the interaction pattern between a technical system and the driver for passive and active safety systems (Hesse, et al., 2011; Mäkinen, et al. 2010).

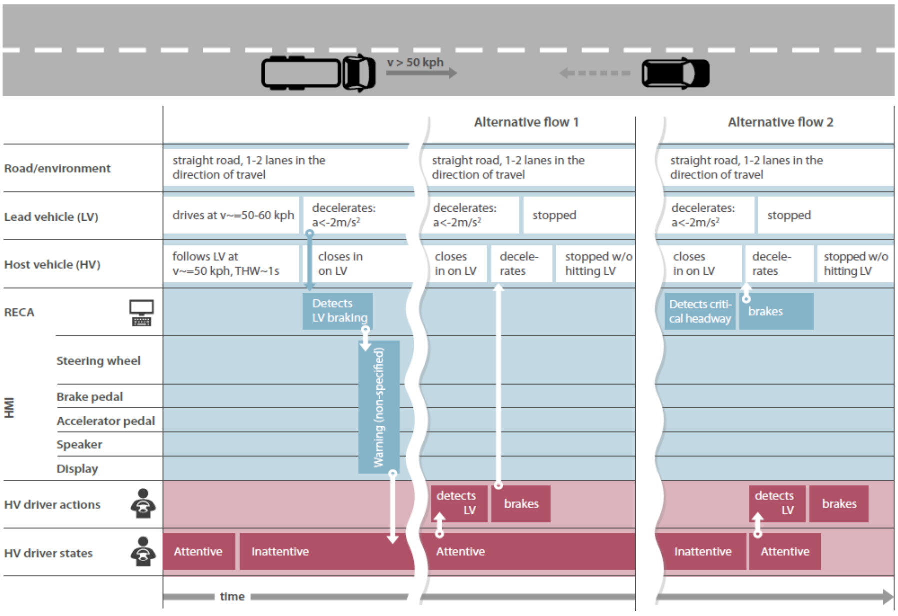


Figure 4 Use case example from AdaptIVe for rear end collision avoidance (Mäkinen, et al. 2010)

Information captured in NDD can serve as input when *developing proper driver-, system-, vehicle- and environmental models* for pre-crash and crash simulations (e.g. Gordon et al., 2010), e.g. for calibrate and validate parameters used in the models. The driver-, system-, vehicle-and environmental models could also be used in the iterative evaluation during development e.g. in order to tune certain parameters.

NDD can be used in order to *evaluate the safety performance of a specific driver support function* in production vehicles.

Ljung Aust (2012) brings up pitfalls and challenges when trying to *evaluate effects* of a single support function when functions are often sold in bundles (e.g. adaptive cruise control, emergency braking system and forward collision warning together with some sort of lateral support).

One way of assessing the effectiveness as well as possible negative effects of introducing a certain countermeasure is via virtual simulation tool (van Noort, van Arem, & Park, 2010). By doing so, research innovative concepts and applications can be assessed in a more flexible, cost effective and safe way (ibid.).Traffic simulation can be used to estimate the network level impacts of a system such as C-ACC (Cooperative Adaptive Cruise Control) and in this way, one can easily experiment with penetration rates or system settings to create hypothetical future scenarios (ibid.) van Noort, van Arem, and Park (2010) describe the required different features of a simulation tool and one of them being a “Driver behaviour model library, containing models that describe the behaviour of drivers at various levels (strategic, tactical, operational) and in various circumstances (traffic situations, weather, ITS applications, etc), and depending on driver characteristics and driver state.” This ‘library’ can be filled with data coming from naturalistic driving studies. A better way to phrase this is that the ‘library’ can be filled with models that describe different types of driving behaviour in different driving conditions and these models can be developed based on NDD (ibid.).

A simple example can illustrate this. Curve driving is not always included in simulation tools (VTI RuTSim model; Tapani, 2005; Tapani, 2008). NDD can be used to analyse curve driving behaviour. A model can then be developed to describe curve driving behaviour for curves with different radii and different maximum speeds. This kind of modelling applies to driving behaviour on different road types and locations (curve, straight, intersection, etc) and under different wheather conditions. In this way this kind of simulation can then be improved and the results are more relilable (see also UDRIVE D53.1).

Figure 5 provides an overview of a virtual simulation framework developed in the V3Safe proposal (2016) to assess the effectiveness of system concepts for the protection of vulnerable road users. For a set of selected use cases (the combination of a scenario and a safety concept), (i) descriptive models for the scenario and road layout, (ii) the behavioural models for the car driver and the VRU, and (iii) the vehicle dynamics models for the passenger car or truck and the possible transport means of the VRU are coupled in a *baseline simulation* (ibid.). This dynamic simulation then covers the last seconds in a potentially hazardous situation for a VRU in interaction with a car (or truck) from a selected starting condition until the moment of collision, or the moment that the collision between car and VRU has been avoided (ibid.).

An overview of the virtual simulation framework from V3Safe is depicted in Figure 5. It distinguishes different “libraries” for the scenario, driver and vulnerable road user model, vehicle dynamics model library, sensor model library and (VRU) safety concept model.

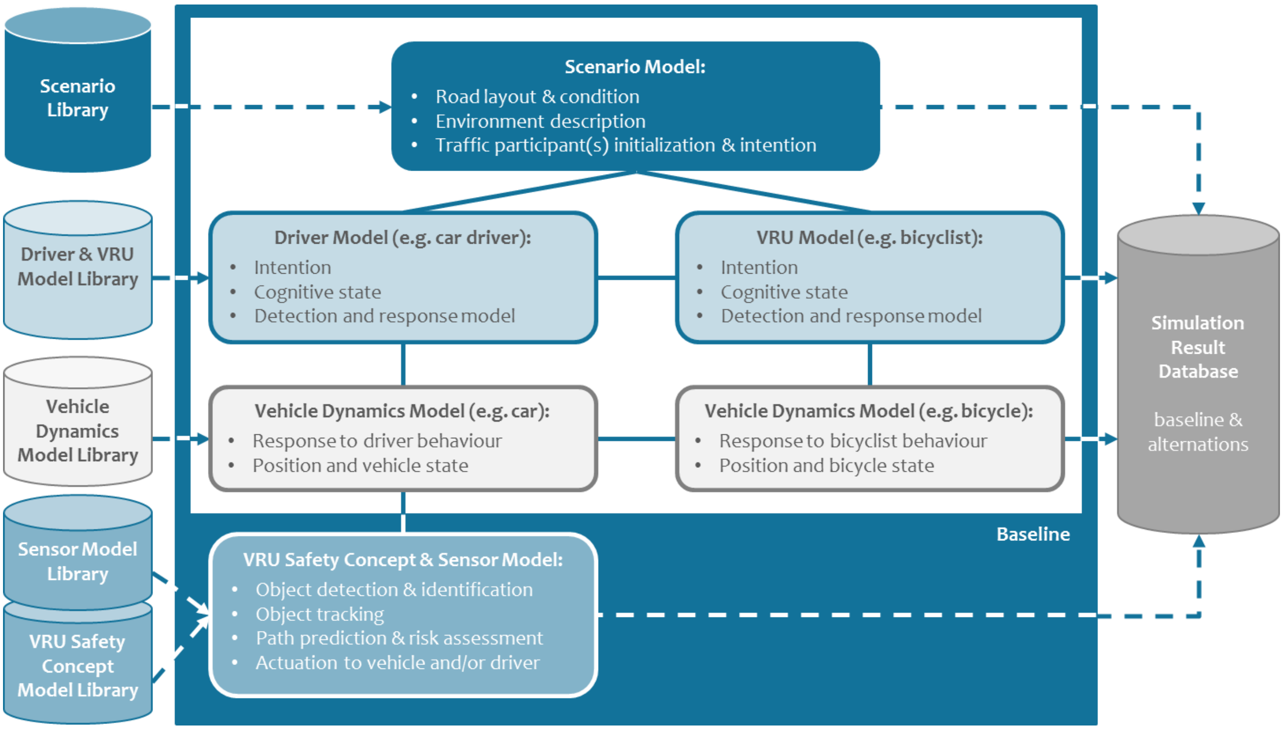


Figure 5 Components of a virtual test environment (from V3SAFE proposal)

The first three libraries will mainly benefit from ND data. In the scenario library different driving scenario's encountered are described in detail (see also de Gelder & Paardekooper (2017) describe the advantage and challenge of scenarios based on NDD. "All assessment methodologies use so-called test-scenarios for which some resulting metrics are compared with a reference..... These test-scenarios can be knowledge-driven or data-driven. A drawback of knowledge-based test-scenarios is that it does not allow to generalize the results to the performance of the system-under-test when operating in traffic, i.e. the test cases may not be valid or representative for real-life traffic. A data-driven approach does allow to generalize the results, but here the challenge is to extract the interesting, e.g. performance critical, test-scenarios from the data, such that the number of the simulations is still limited." Examples of 'data-driven approach' scenario's are shown in Figure 6. In this case the scenarios are described by three 'dimensions', host-vehicle (driver and vehicle),active environment (other road users), and passive environment (road elements and weather). A scenario is then "the combination of actions and maneuvers of the host vehicle in the passive environment, and the ongoing activities and maneuvers of the immediate surrounding active environment for a certain period of time"(Elrofai, Worm, & Op den Camp, 2016). A scenario could then, for example, be a driver driving on the motorway in rain or a driver on a rural road in sunny weather overtaking another vehicle[1]. Depending on the NDS (e.g., where and when data is collected) many different scenarios can be obtained from NDD.

As in the simulation tools described above models depicting driving behaviour and driver behaviour are needed in virtual testing as well. To assess the benefits of an ADAS it's necessary to know how drivers behave in specific situations and how drivers react to the interventions by their vehicle. Also it is relevant to model driver's state (e.g., distracted, fatigue, drunk) and to model the behaviour of other road users. Most of these models still need to be developed since models are either descriptive and can therefore not be used or are very specific (e.g., near collision behaviour models; see e.g., Markkula et al., 2012). NDD (with or without systems) can then provide the relevant data to develop, test and validate the behaviour models.

[1] See Elrofai, Worm, & Op den Camp, 2016 for more information on scenarios and how to extract them from NDD.

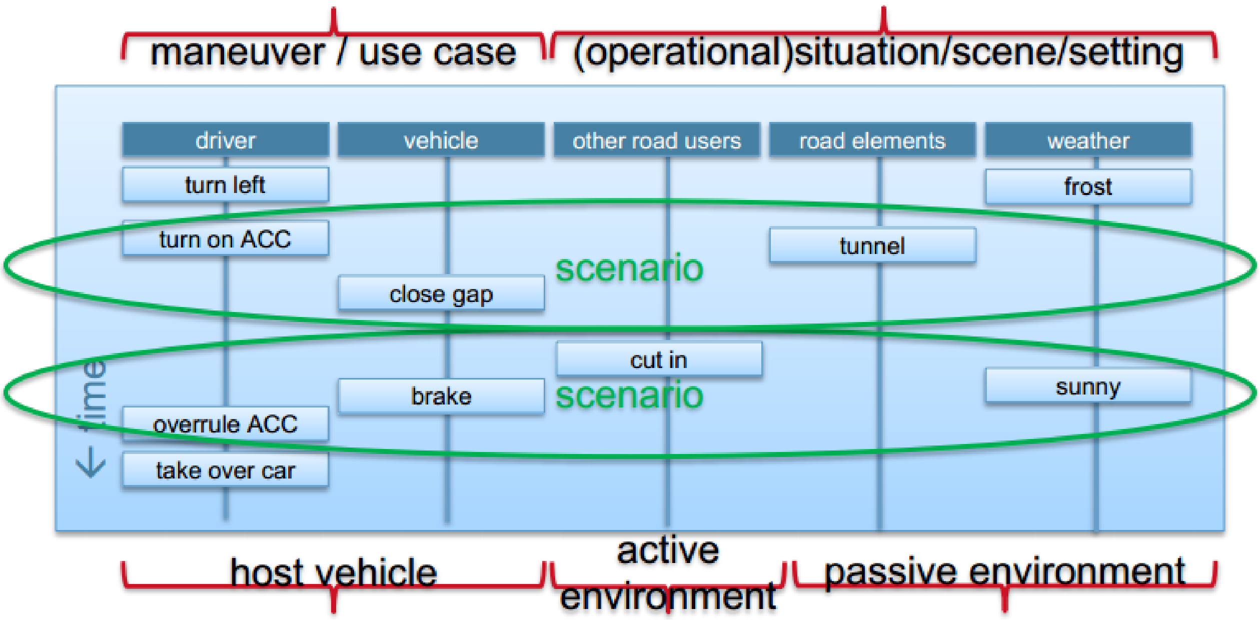


Figure 6 Different possible scenario's

The P.E.A.R.S. network is currently working on creating harmonised methods and tools with the main objective to create a harmonised *effectiveness assessment framework* including evaluation scenarios (e.g. type of road, visibility conditions, traffic density, …), driver models (e.g. driver reaction), vehicle performance models as well as combinations of all these mentioned and finally create quantitative assessment of traffic safety impacts such as system benefits as well as risks (accident and incidents avoided or mitigated as well as possible negative effects of newly created incidents or accidents). (Page, et a., 2015). One of the motivational factors is the non-harmonised way of working today with large variety of data sources (e.g. accident data, driving simulator data, FOT and NDD data, EDR data, traffic observation data) and tools being used (e.g. Matlab, Simulink, PC Crash, MADYMO, CarMaker, PreScan). The issues with regards to this variety are for example the difference in how evaluation questions can be posed, how a baseline can be established and the way results can be interpreted. OpenPASS (openPASS, 2017) is an initiative established by Daimler, VW and BMW in order to harmonise simulation tools and create a new software framework for simulation and evaluation of active safety and different types of automated functions. The idea is to cover all relevant characteristics including driver, vehicle and environment variables and use the results from in system development and optimization, safety assessment, when creating proof of concepts as well as in research (ibid.).

2.1 Requirements of naturalistic driving data

The following information is collected from ND studies in all stages of driving from critical driving to normal every day driving to support the development of functions:

- Driver state and driver behaviour/response in relation to different sources of information (e.g., the view on the road, the HMI of the vehicle, any nomadic devices that are being used).
- All the different scenarios that occur on the road, that need to be interpreted correctly by sensor systems with respect to all road users that are, will be or might be in direct interaction with the host vehicle. Each drive on the road is considered as a series of (possibly partly overlapping) scenarios. Within these scenarios, an ND study should provide the characteristics of the surrounding traffic participants (type, trajectory with respect to the host), basic infrastructure features that influence the behaviour of the road users (view blocking obstructions, lane and line markers, traffic rules, traffic lights), and environmental factors such as weather conditions and lighting conditions.

In naturalistic driving studies, there is no focus on the response of the vehicle to the different situations and scenarios that occur on the road. Such information is obtained through for system evaluations in field operational tests.

Depending on the level of automation for which an analysis is performed, focus is on the driver response and/or on the characterisation of scenarios:

1. The main issue in driving behaviour research is to be able to ascribe a change in behaviour to a single specific change in the outside world (e.g., decreased swerving due to smaller lane widths). In order to be able to do this in an ND study lots of data needs to be collected. Definitely cameras need to be installed providing an outside view, an inside view, and a good view of the driver and the drivers' eyes. The latter is especially relevant to measure distraction, and fatigue. Besides the video recordings the following signals are minimally needed to classify and understand driving behaviour
    a. GPS
    b. Steering wheel (10Hz)
    c. Speed (10Hz)
    d. Lateral position (10Hz)
    e. Radar (10Hz)
    f. Weather / road conditions
    g. Vehicle state parameters

    Also data needs to be collected on the drivers with respect to, for example, skills, personality traits, personal data (age, driving experience, years driving license, etc). Standardised questionnaires are available.
2. To collect, identify and classify scenarios out of naturalistic driving studies, the following signals need to be recorded from the perspective of the host vehicle:

    <u>Host vehicle</u>:

    - Trajectory (position on the road, speed, heading, yaw-rate, acceleration/deceleration, GPS-position as function of time);
    - Vehicle state parameters (usually from the vehicle CAN-bus, on which e.g. gas-pedal position, brake pressure, steering wheel angle, blinker operation, wind shield wiper operation, actual fuel consumption, trip fuel consumption etc. is found);
    - Additionally, parameters such as mass of the vehicle and the characteristics of the vehicle sensor system (for each sensor: range, view angle, delay, location and viewing direction, and the accuracy for determining surrounding objects) need to be known.

    <u>Road users surrounding the car from the car sensor system</u>:

    - Type of traffic participant – pedestrian, bicyclist, passenger car, moped, motor cycle, truck, mobility scooter, etc.;
    - Trajectory (position, speed, heading, yaw-rate, and acceleration/deceleration relative to the host vehicle) and the location on the road (e.g. with respect to the road side, or line markers).

    <u>Environment & infrastructure</u>:

    - Type of road, number of lanes, line/lane markers, road edge, side walk, bicycle lane;
    - Traffic lights and traffic rules;
    - Static objects (e.g., blocking the view, influencing the behaviour of road users, disturbing the input to sensors).

    <u>Disturbances due to weather & lighting conditions</u>:

    - Visibility issues due to precipitation or fog, incl. visibility of line and road markers;
    - Lighting conditions (e.g. low light, glare)

3 Using ND data for behaviour-based safety programmes

In general, ND data can facilitate more efficient development of crash/injury countermeasures by identifying and focusing on the most important safety (crash) problems. As one example, the 100-Car Study was intended to generate detailed information about the factors that may play a role in the occurrence of crashes or near-crashes (Dingus et al., 2006). In total, data has become available about a distance of two million kilometres driven, on which seventy crashes occurred (of various degrees of severity; Neale et al., 2005). The most important outcome of this study was that in almost 80 percent of all the crashes (observed in this study), distraction or inattention (three seconds prior to the crash) played a role.

3.1 ND data for changing habits and for enhancing coaching strategies

Even though the accident statistics are still unacceptably high (26,300 people lost their lives on EU roads in 2015 (European Transport Safety Council, 2016)), humans are very good in preventing crashes. ND data can be useful to help researchers understand some profound questions such as: What shapes that behaviour? What are the mechanisms of the driver's reaction seconds prior to a crash? What are the mechanisms of the driver reaction for successfully avoiding a crash? How can the reaction be predicted? If ND data supports to enhance the knowledge for answering these questions, successful driver coaching programmes can be developed. Driver coaching programs are behaviour-based programs during which behaviour is defined, monitored, recorded and evaluated. After evaluation, feedback is provided on this behaviour with the goal that undesired behaviour is not likely to be repeated in the future. The provided feedback can be immediate or in retrospect and can be provided via technology or a human coach. A more detailed description of the main principles of behaviour-based services together with the barriers to application in the automotive domain is identified by Wege (2013).

In order to shape custom-made behaviour-based driver coaching, in-depth behavioural knowledge is required. A major part of this in-depth knowledge is to comprehend the mechanisms of driver behaviour. One example of the reason why it is necessary to comprehend specific behaviour is to successfully avoid a precipitating event, in other words understand behaviour in safety critical events that *do not* lead to a crash event, so called "behavioural" events (Wege, 2013). The understanding of what types of behaviour lead to a "behavioural event" in connection with the *specific behavioural mechanisms* that actually lead to the prevention of a crash is particularly important. Specific behavioural mechanisms can be for example situational mismatches between proactive schema selection and the actual situation (Engström, Victor & Markkula, 2013) from a depleted situation model (e.g., Horswill & McKenna, 2004)? The preventive behavioural mechanisms (automatic or intentionally) are the mechanisms that should be coached on. Previous research suggests that these behavioural mechanisms can be found in "precipitating" events. The consideration of behavioural strategies in lower-risk driving may lead to an increased understanding of successful avoidance of threats offered by a precipitating event. In general, the x-seconds prior to a precipitating event have been of particular interest in recent projects which also collected ND data (such as the glance data collected in the 100-Car Naturalistic Driving Study (Dingus et al., 2006)). Thus far, the results retrieved from the analysis of the short time-span before a precipitating event has been often used for understanding crash causation (e.g. Victor et al., 2015), however has been used little for enhancing coaching strategies of behaviour-based services – a gap that needs to be tackled in future research. ND data can offer important insights into enhancing this knowledge.

Two specific use cases showing the value of ND data for enhancing coaching strategies for driver coaching programmes are coaching teen drivers (e.g. Carney, McGehee, Lee, Reyes & Raby, 2010) and coaching commercial truck drivers. The latter will be discussed in more detail in the sections below. Coaching programmes can also include self-coaching and self-evaluation awareness. The concept of self-coaching could be of importance for usage-based insurance offers. The main function of self-coaching is to create self-awareness of one's own driving style and safety critical behaviour.

In sum, the main value of ND data for behaviour-based programmes is the identification of behavioural mechanism in a beh99999avioural event precipitating a safety critical event (prevented crash).

The intended results of coaching programs are the formation of new habits. This should be accompanied by a change in attitude, feelings, stress level, and self-perceived performance on the coaching targets. Volvo has developed a concept called Integrated Driver Coaching Program which aims to assist drivers and their fleets to change their mal-functioning habits by applying a cross-disciplinary behaviour change framework. Combining technical and psychological/therapeutic principles for driver coaching should lead to a more sustainable habit change (Wege & Babel, submitted). Habit change is based on change management which is a concept that exists in a wide variety of fields (e.g. clinical and health psychology, organisational management and sports). A prerequisite for initiating a change in habits is to fully understand a drivers habits (as mentioned above especially before, during and after a behavioural event which might lead to be a safety critical event or even a crash). ND data can be a powerful source of understanding naturalistic behaviour.

3.2 ND data for coaching for commercial vehicle customer operations

Commercial vehicle research projects that were specifically set up to understand the benefits of driver coaching programmes are the BBS USA Project as a collaboration between AB Volvo and UMTRI University (Pradhan, Wege, Lin & Babel, 2017) and the BBS China project as a collaboration between AB Volvo and Chalmers University and Tongji University (Bianchi Piccinini, Engström, Bärgman & Wang, submitted). Other commercial vehicle research projects include more conceptualised projects that show the challenge of hidden costs of collisions. A result of such a project was that commercial vehicle fleet owners often do not systematically evaluate the safety problem at their fleet – a problem which could be prevented by commercial coaching programs (Löfstrand, Söderman & Stave, 2015; Wege & Pirnia, 2016).

Commercial coaching programs often depend on big data collection. Fleet operators become more and more depended on the analytics work of big data of commercial vehicle OEMs. Big data, for instance, has the power to shed light into the causes and prevalence of accidents on a bigger scale. From the prevalence, we can draw conclusions on the consequences (e.g. socio-economic consequences) followed by providing suitable solutions (foremost formulating adequate use cases, as explained in Task 5.4.1). ND data, e.g. from the UDRIVE project, can be an important part of a big puzzle for evaluating the safety performance of a customer fleet Figure 7. shows this relationship in more detail. Figure 7 shows the Safety Diagnosis model (Wege & Pirnia, 2016) in which the ND data component is highlighted with red boxes. The *reason why* ND data is important in this context is highlighted with a green box in Figure 7. – the reason is to establish use cases for service offerings, e.g. behaviour-based services (offered by OEMs or third-party suppliers)-. The Safety Diagnosis Model in Figure 7. shows how ND data are not to be considered a method, however are merely a tool which has a systematic place within a big "safety-analytics picture".

ND data could be used as a baseline data set for fleet management systems or can be used as simulation data to test functionalities for detecting critical driving behaviour like harsh braking and sudden steering. The Fleet Management Systems Interface (FMS) is a standard interface to vehicle data of commercial vehicles. The six European manufacturers Daimler AG, MAN AG, Scania, Volvo (incl. Renault), DAF Trucks and IVECO have developed the FMS-Standard in 2002 to allow 3rd party telematics solutions access to key vehicle data through a set of standardised FMS datagrams. All other datagrams on the CANBus are proprietary to vehicle manufacturer and typically not published.

The data are coded according SAE J1939. The repetition rate of the data is between 20ms (e.g. engine speed) and 10 sec. (e.g. vehicle identification number). The amount of data is dependent on the manufacturer and model of the vehicle and might be different. If some data are not available at the interface they are marked as not available.

A direct connection to the internal vehicle bus system is not permitted by truck manufacturers as it could compromise and can lead to the loss of warranty. Some manufacturers are restrictive in their workshops and cut all unknown connections to the internal bus system. The FMS Gateway implements a vehicle manufacturer certified 'firewall' interface between the vehicles internal controller Area networks (CANBus) and external 3rd party equipment connected to the gateway. This enables devices to be safely connected to the CANBus without the risk that they can transmit data onto the CANBus or interfere with the communication between vehicle ECUs on the bus.

FMS can be used by fleet owners, non-professional or a professional drivers to improve their driving skills, and prevent accidents. This is done by measuring the driving characteristics, which can be assessed by information from the CANBus, such as lane keeping, abrupt braking frequency, speeding percentage, coasting percentage, and fuel efficiency. While driving, stationary sensors on the vehicle, as well as fatigue related information that can be obtained from the CAN-bus can also be valuable as indicators for driver fitness. Feedback on their driving behaviour can be used to coach drivers to drive more fuel efficient and/or safely, or to enrol them in specific training programmes.

Wege and Pirnia (2016) together with their team that defined the importance of target-scenarios and use-cases argue that only a disciplined and structured approach to commercial vehicle safety can lead researchers and practitioners to offer the best BBS services. ND data is also an important part of this approach. Until recently, there did not exist a solid methodology for identifying the safety problem at a customer fleet. Generally, it is easier to identify the mere number of accidents or even the type of accidents (e.g. rear-end damage when backing up at the customer site). In comparison, it is a challenge to identify causes and consequences (outcomes such as costs) of accidents without having a solid accident analysis methodology in place. The Safety Diagnosis model (Wege & Pirnia, 2016) (Figure 7) proposes a step-by-step approach for such an analysis. The model is divided into "long-term safety investigation of general fleet safety situation" (upper horizontal row of the model) and "short-term investigation on one incident/accident" (lower horizontal row of the model) at a fleet. For both types the cause and prevalence of the accident need to be investigated using various methods that are described in the model (e.g. obtaining fleet records, observations, or interviews). This problem analysis is using a holistic approach by identifying also psychological concepts (e.g. identification of staff moral) and organizational culture (e.g. safety culture, off-the-job safety or practices of staff screening such as their experience or health). The consequences of the accident(s) are identified in-depth at the next stage. For the general and more long-term safety investigation type this leads directly into the solution stage where solutions are proposed (e.g. service offerings). For the short-term accident investigation on one accident case the next step would be a case description of the scenario of the accident. This case description is split into an accident reporting (e.g. using the DREAM interview methodology (Habibovic, Tivesten, Nobuyuki, Bärgman & Ljung Aust, 2013)) and a collision cost report (e.g. using a cost report suggested in the SRM II project (Löfstrand, Söderman & Stave, 2015)).

The Safety Diagnosis model covers steps I to VI:

I. Problem definition (incl. defining a target scenario),
II. Method
III. Tool

IV. Cause (either sharp end or blunt end) and prevalence
V. Consequence (including the Iceberg Model on various hidden and open collision costs)
VI. Solution (incl. defining a use case)

The tools of “observation” (using telematic systems and or recorded video footage as described below) are particularly related to ND data. With these tools, steps IV.-VI. of the model can be systematically explored. However, before even reaching step III. (tools) it is important to define step I. and step II. Especially the definition of a target scenario (step I.) is key for a solid ground of using the model further. As the model shows ND data are an important tool for both “long-term safety investigation of general fleet safety situation” (upper horizontal row of the model) and “short-term investigation on one incident/accident” (lower horizontal row of the model) at a fleet. For more information on the Iceberg Model of safety associated costs depicted in the model, see Wege and Pirnia (2016).

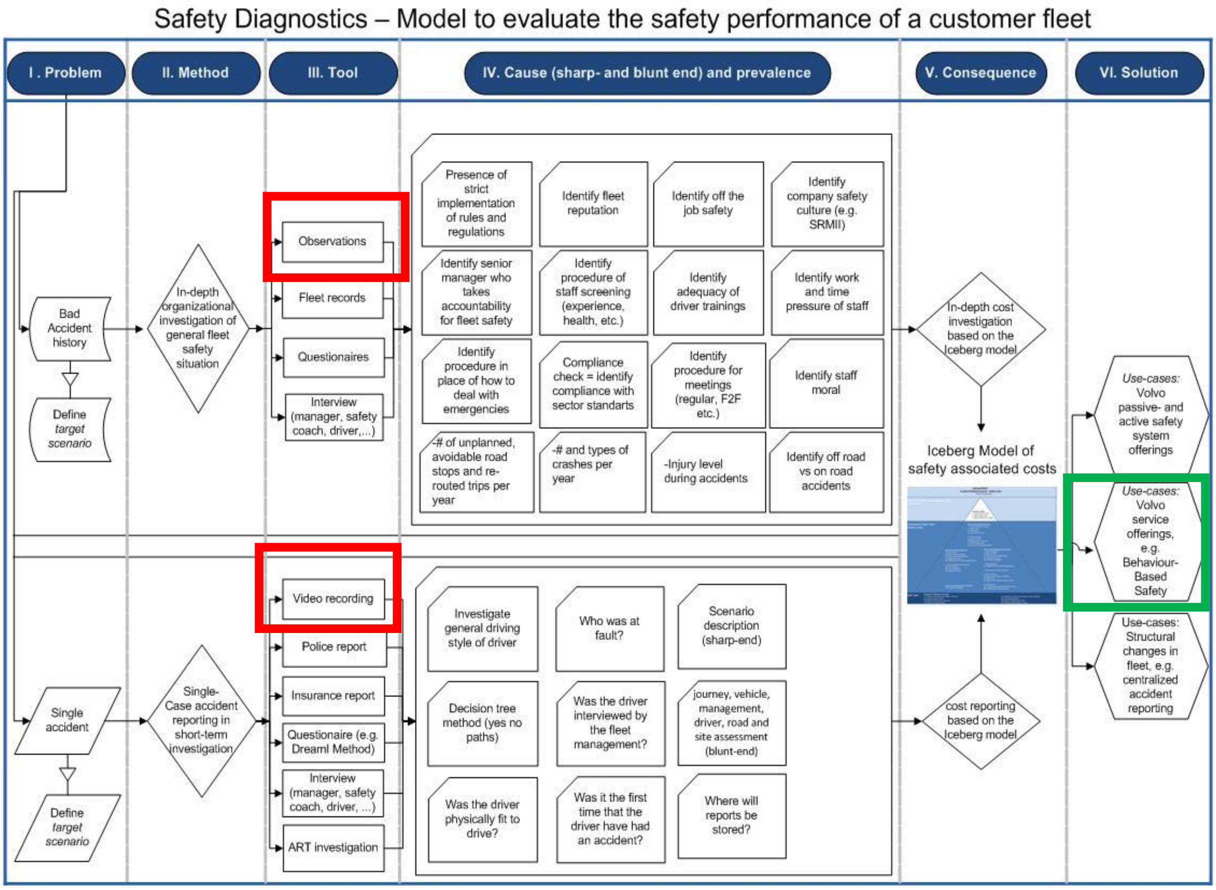


Figure 7 Customer Safety Analytics Methodology – A Model to evaluate the safety performance of a customer fleet (The related boxes for “tools” for ND data are marked in red and the related solution is marked in green), Wege & Pirnia (2016)

3.3 ND data for Driver training and education

ND data can help define specific education and driver training aimed at specific type of risky drivers like novice and teen drivers (e.g. Carney, McGehee, Lee, Reyes & Raby, 2010) or older drivers (e.g. Ott, Davis & Bixby, 2017). ND data can then be utilized to develop adequate countermeasures for risk full behaviours e.g. drowsy driving and distraction. Understanding the prevalence of potential contributing causes of crashes provides a significant societal benefit and advances the field of traffic safety. For example, Carney et al.

(2015 AAA foundation) did a large-scale comprehensive study of naturalistic data from thousands of actual crashes involving teenage drivers. The ND data allowed to examine behaviours and potential contributing (environmental) factors in the seconds leading up to the collision, and provided specific and detailed information not available in police reports. More specifically, unique information regarding what is happening inside the vehicle during the seconds before a crash became available.

They found that conditions leading up to a crash varied substantially especially environmental and roadway conditions per crash type (Carney et al 2015). Single vehicle crashes were most affected by weather and surface conditions. With single-vehicle crashes time-of-day also played a role, i.e. accidents were more likely to occur at night, while vehicle-to-vehicle crashes were more likely during the day with high traffic flow. Also recognition errors were more common for vehicle-to-vehicle crashes, while performance errors were more frequent in single-vehicle crashes. Behaviours leading up to a crash were divers but the most common behaviour among young drivers was attending to passengers most often having a conversation with the driver. Cell phone use was also seen frequently for all drivers, with operating/looking at the phone (e.g., texting) observed most often. The use of a cell phone use contributed to significantly longer reaction times. The authors argue that potentially distracting behaviours in general, and cell phone use in particular, are much more prevalent in the current study than in official statistics based on police reports. Thus ND data gave much more insights in the scale of distraction during driving. One unexpected result was that reaction times were not significantly longer when drivers were attending to passengers than when they were not. The results of this study (Carney et al 2015) can be used to inform the development of education, training, and technology-based interventions specifically aimed at reducing teen drivers' crash risk.

3.4 ND data in existing safety programs and driver coaching programs

The combination of technical solutions and coaching is called behaviour based solutions. An overview of the state-of the art existing solutions for driver coaching for a) telematics and on-board systems (Camden, Jeffrey & Hanowski, 2015), b) driver trainings and c) their symbiosis can be found in Wege and Babel (submitted). For BBS it is key to integrate stakeholders (driver, coach, fleet, organization), to integrate the target of the coaching (safety, fuel consumption. vehicle care, driver health, custumer communication and stress management).

For successful safety programs and coaching programs during which timely and effective feedback to the driver is provided, it is necessary to track reliable ND data. Usually two types of data are tracked. One type is video footage of a few seconds of a safety critical event (e.g. Lytx Drive Cam System or SmartDrive). Another type is data from telematic devices. A telematic device monitors, records, displays and alerts with regard to key performance indicators (KPIs). KPIs could be fuel consumption, safety and/or vehicle care. The sub-KPIs for fuel can be unnecessary fuel consumed during braking, acceleration, over speeding, idling or coasting. The sub-KPIs for safety could be compliance with speed limit, Time Headway (THW), attention to vehicle control, safe cornering, seatbelt usage or braking behaviour. Along with the KPIs and sub-KPIs data from GPS Systems should always be recorded. Some comments about the related privacy issues etc. can be found in Task 5.4.3.

The telematic device handles the incoming vehicle-data and performs the calculations of the KPIs in order to classify them into good behaviour/acceptable behaviour/bad behaviour etc. Further, telematics devices provide the opportunity for various feedback timings. Apart from live feedback, the scores can be stored for post-trip feedback. An overview of the different types of feedback categorised into I. Concurrent feedback, II Delayed feedback, III. Retrospective feedback, IV. Cumulative feedback and V. Deferred feedback can be found in (Donmez, Boyle & Lee, 2008). A further adaptation of these feedback categories along with their application to accident prevention before, while and after driving can be found in the DO-IT BEST Feedback Model (Wege & Victor, 2013). The basis for the DO-IT BEST Feedback Model are original BBS literature from industrial work settings (Geller, 2001). Geller was among the first who introduced the behaviour-based solutions concept into work safety in factory settings and occupational behaviour research. For factory workers to operate more safely, their behaviour had to be first well defined followed by it being observed in real working settings. Transferring this approach to the automotive context created the use case for ND data in the UDRIVE project. Data needs to be defined and observed (monitored) as a prerequisite for any type of coaching. At a later stage, ND data needs to be annotated. Several projects have aimed at creating code books to annotate video data to be used for analysing behaviour on a broader scale (e.g. ANNEXT (Engström, Werneke, Bärgman, Nguyen & Cook, 2013) or DREAM (Habibovic, Tivesten, Nobuyuki, Bärgman & Ljung Aust, 2013)).

3.5 ND data for improving fuel efficiency

LeBlanc (2010) studied fuel efficiency with ND data. While some of the obtained variation in fuel economy is likely due to uncontrolled or unmeasured factors, such as passenger, geography, fuel weight, and wind, the data imply that the behaviour of real-world drivers adds significant variation to fuel consumption rates. The findings suggested the possibility of substantial potential gains in real-world efficiencies through modification of driver behaviour itself, or for electronic modulation technology between the driver's foot and the throttle to modify a relatively wasteful driving style into a more efficient one.

3.6 ND data for validation of existing models

Naturalistic Driving provides the opportunity to assess to what extent model-based calculations correspond to the daily practice of traffic participation. A survey among potential users of Naturalistic Driving research (Van Schagen et al., 2010) indicates that they are also interested in these types of application i.e. human behaviour in relation to environmentally friendly driving and traffic flows Figure 8.

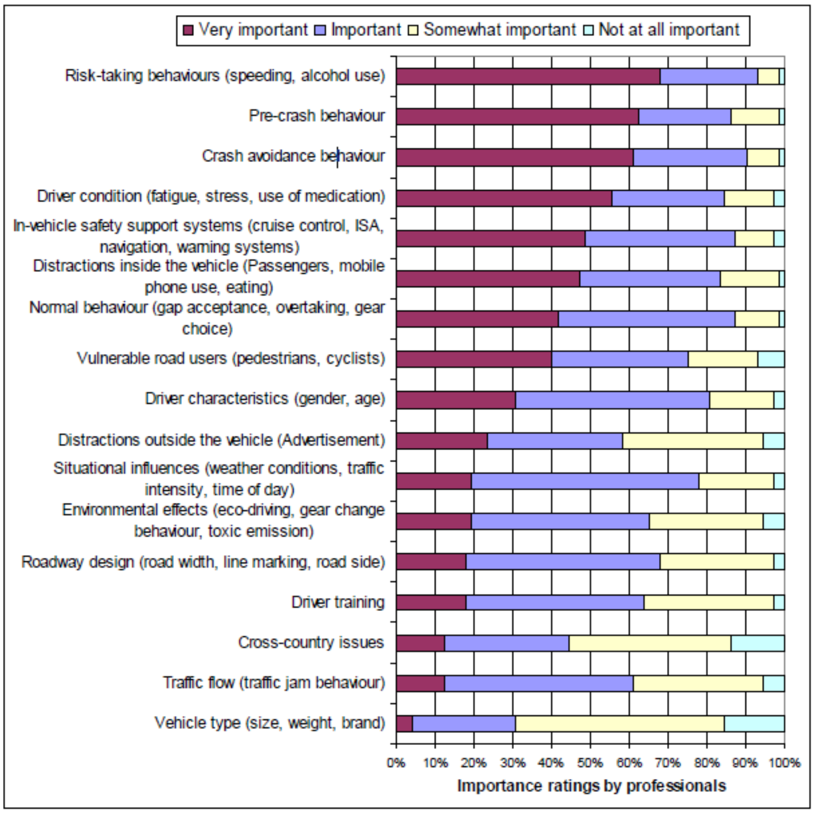


Figure 8 Survey among potential users of Naturalistic Driving research (Van Schagen et al., 2010)

4 Business models

Naturalistic Driving Studies and Field operational Tests have been emerging in the past decade as a new tool to understand driver's behaviour or driver's usage and acceptance for a specific vehicle function. Projects like EUROFOT, TELEFOT, DRIVE-C2X, UDIRVE have all collected huge amount of naturalistic driving data. The projects have used similar methodologies to make sure the long and demanding data collection phase is well prepared and the resulting data leads to the expected answers to the Research Questions (FESTA Handbook, version 6, 2016).

The methodology also describes how to get the consent from the drivers to exploit the data for research purposes; it is indeed essential that the collected data can be used beyond the project itself. Even though the term "research purpose" may be subject to long interpretations, we may consider that industry research is included in this category which would open the possibility to exploit the collected ND data for other communities than the traditional human factors, traffic specialists and/or ergonomist research community.

Over the past years, the principle of data sharing became more and more prominent as the project FOT-NET Data was making progress as more collected data is being shared. Different trends are converging: the cost of storage, the computing power, novel semi-automated annotation techniques and very importantly the mind-set; all of it makes it easier to exploit the full potential of ND data. Issues related to documentation, anonimization, maintenance, analysis tools are gradually being clarified partly thanks to the common efforts to update the FESTA methodology and its promotion.

However, questions remain: Why do we need to share data? What for? How to make data sharing viable? What are the financial models that could be applied?

- **Competitiveness through reuse**

Firstly, for any new Field Operational Tests, it will become increasingly difficult to justify ND data collection for baseline comparison. Re-use of ND data should be considered as a background resource to a new project for which a baseline is required for comparison purpose. Typically, a study of the impact of an automated driving function would include an extended pre-study on the basis of previously collected ND data.

- **Re-use purpose**

Secondly, the way the ND data is re-used was most of the time not originally foreseen. A new project would typically analyse the data from another angle where only a part of the data is re-used probably combined with other data sets. Data sharing therefore unleashes the potential of the collected ND data without competing with the interests of the ND data original "owner". It is even more true when analysis techniques and tools are also shared among the community.

- **Future proof**

Finally, new digital infrastructure built around data sharing should be considered as an investment for the future. All indicators point at the collection of an exponentional amount of road data from vehicles, roads, and drivers. The data infrastructure should be scalable to accommodate new ND data and flexible to adapt to new formats. Any new ND datasets should be easily integrated together with metadata and annotations.

4.1 View of the industry and research centres on the re-use of ND data

UDRIVE partners have consulted a series of potentially interested companies who could benefit from ND studies. In total, we received nineteen responses some of which were followed up with phone conversations on the basis of the answers received (see next paragraph). Additional phone conversations took place in order to complete the industry representativeness of the sample. The figures below(next paragraph) are therefore not fully representative but give an idea of the trends.

Even though the questions were directed to the industry and the possible use of the ND data for industrial research exploitation, the majority of survey feedbacks came from applied research organisations working in direct relation with industry (42%); next category was the automotive industry (OEMs & suppliers – 32%) followed by service providers. Research organisations are indeed the most likely customers for such ND data analysis. They may even have the know-how to analyse it without requiring specialist support.

Most of the consulted parties (90%) knew well what ND data was and had experience collecting such data through internal projects or via collaboration with research centres. They consider the collected data was a key to achieve the original objectives of the specific project. In general, the reuse of the data was very low after the end of the project. But, as a whole, the industry is generally unaware of the potential of ND data to make evidence-based designs, decisions and/or policies. For a majority of projects (58%), the ND data was collected in internal projects without collaboration. Whereas the rest collaborated with other research institutes. 80% of the respondent acknowledged that the ND data was essential to achieve conclusive results. ND data collected from customers becomes highly attractive in the future as a sustainable stream of data for continuous product development: 25% claimed they are already collecting a considerable amount of data from their product but it is less clear how much this is linked to products improvement or development.

Potential application developments which were mentioned are Cooperative, connect & automated driving, ADAS, traffic safety, risk assessment, usage data, effects of regulations, driver distraction. Also, Video analytics and algorithm development were cited.

The highest interest for in-vehicle data was from CAN, radar and cameras (oustide and driver views). There is a growing interest to access (historic) probe data, which is considered to be highly valuable to understand traffic bottlenecks or mobility patterns, but there are little attempts to use ND data to get an insight into what the drivers are actually doing on different types of roads or how the drivers are interacting with their vehicle and the road environment. The potential is however perceived by the parties but they see so many legal and practical hurdles to access such data that it easily gives up along the way. A recurrent issue mentioned by the potential ND data users is their lack of expertise to analyse the data. The community at large would welcome any improvements to access collected ND data but the lack of expertise seem to remain the greatest issue.

For the ones who have ND data analysis expertise, their main plea is to have a one-stop European approach where many different data sets can be shared with economies of scale on the data infrastructure and required computing power. If a data infrastructure would exist, a give and take model seemed to be the most likely: the parties expressed their interest to share data at the condition that they can access other data sets. However, this model is often challenged by issues such as chicken-and-egg (who shares first?), critical mass (what is the scale of the shared data?) and unbalanced contributions (How to encourage to share more?).

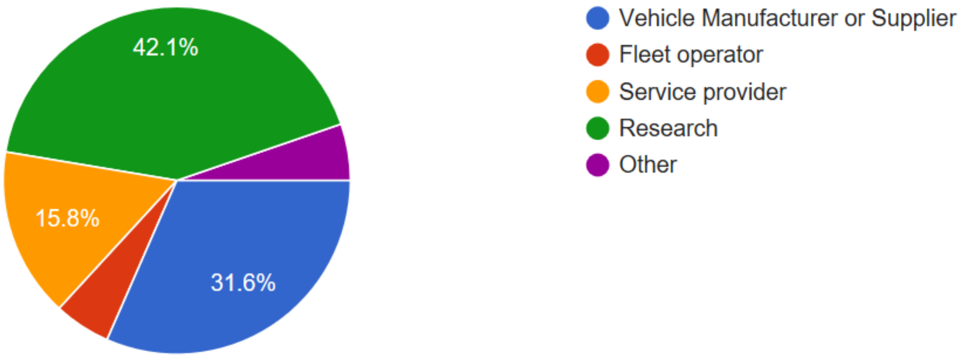
On the willingness to pay, most of the respondent could not express themselves at this stage; 50% remained positive to pay for the access to the data whereas a third preferred an option where they participate commonly to the cost guaranteeing the access to the data. Still, the impression during interviews was that the majority preferred the option of paying for what they ask for rather than having to develop all skills to analyse the data.

4.2 Results business model questionnaire

Below the graphic results of the questionnaire summerized per question is shown. Due to the number and type of responses a descriptive approach is used:

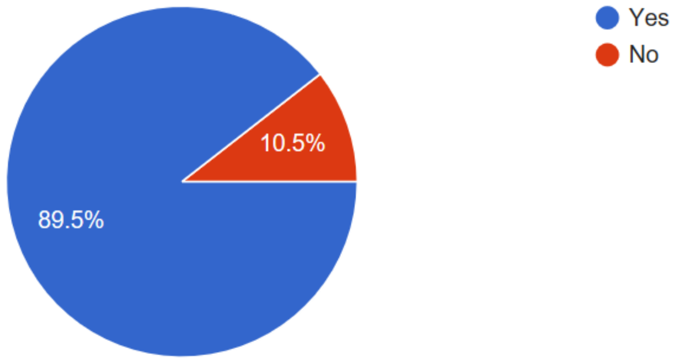
Which sector are you representing

19 responses



Are you familiar with the term of naturalistic driving studies (NDS)?

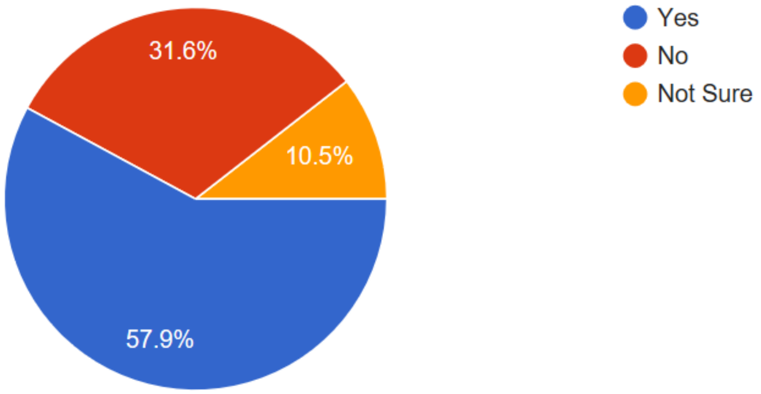
19 responses



Your past experiences with ND data

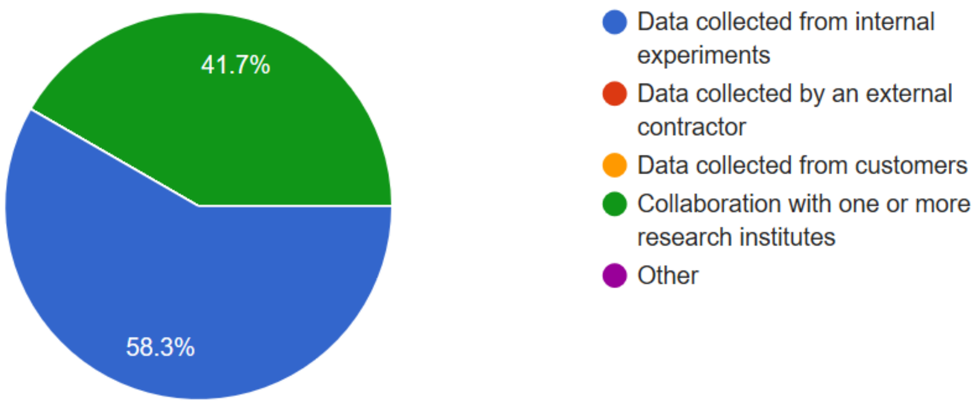
Has your company used ND data for product or service development?

19 responses



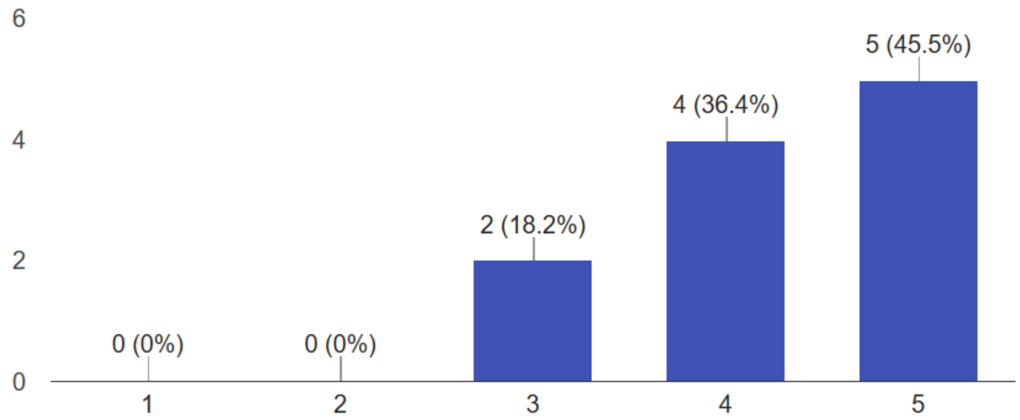
if Yes, how did the company collect the ND data?

12 responses



if Yes, how important was the ND data to achieve conclusive results?

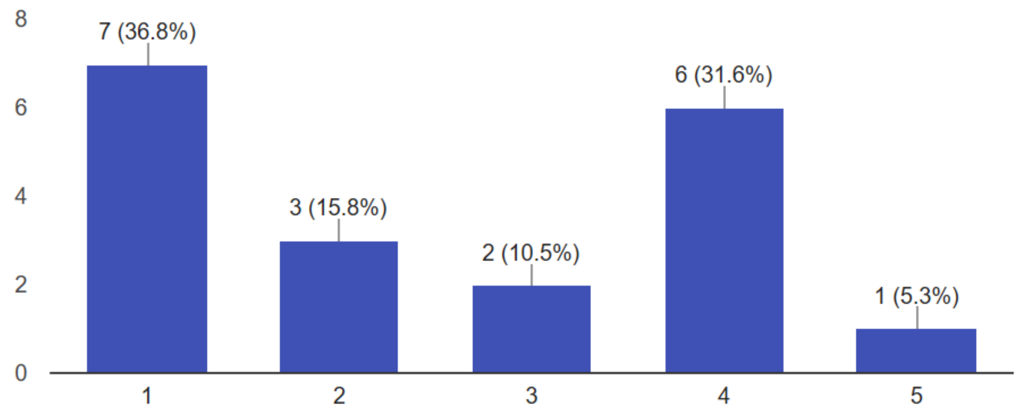
11 responses



“not important” versus “very important”

How much are you using this ND data for product development or usage analysis, etc...?

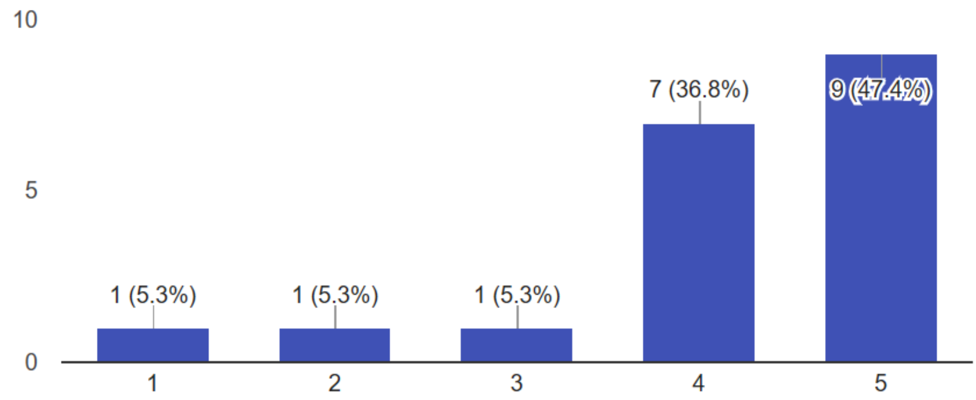
19 responses



“no data” versus “all the data we can get”

How do you value ND data compared to other type of data like crash data, experimental controlled data?

19 responses



“not important” versus “very important”

What kind of product /service would benefit most from collection of ND user behaviour?

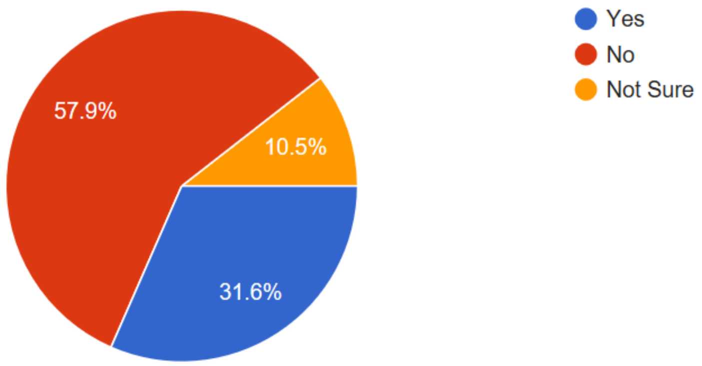
13 responses

Vehicle Automation development and traffic safety
Research
ADAS algorithm
Risk assessment, personalozation of ADAS
ADAS
Image & Video Analytics
ADAS/AD, frequency of use of different functions (e.g. ACC, Cruise control, telematics functions etc).
In our opinion these are crucial gor the effizient and effektive introduction of Automated Driving
New regulation
research
Any to do with vehicle behaviour or infotainment etc. Also passive safety.
machine learning and mobility

Release of ND data from UDRIVE project

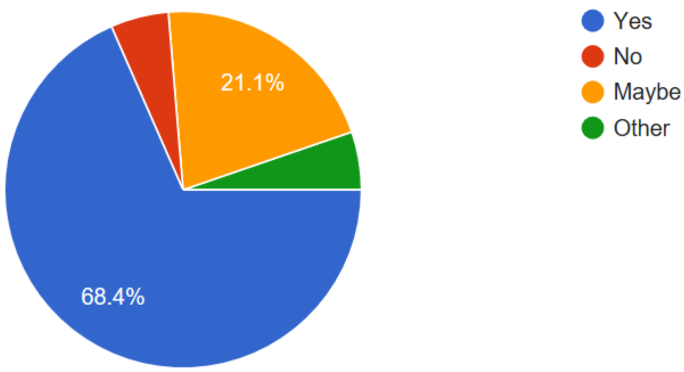
Did you know the UDRIVE project plans to release its ND data after the end of the project?

19 responses



If the UDRIVE ND data is made available: Would you be interested to exploit it?

19 responses



Could you mention additional data that generally lacks in ND data but would be very relevant to increase your interest (e.g., weather data, infrastructure, etc)?

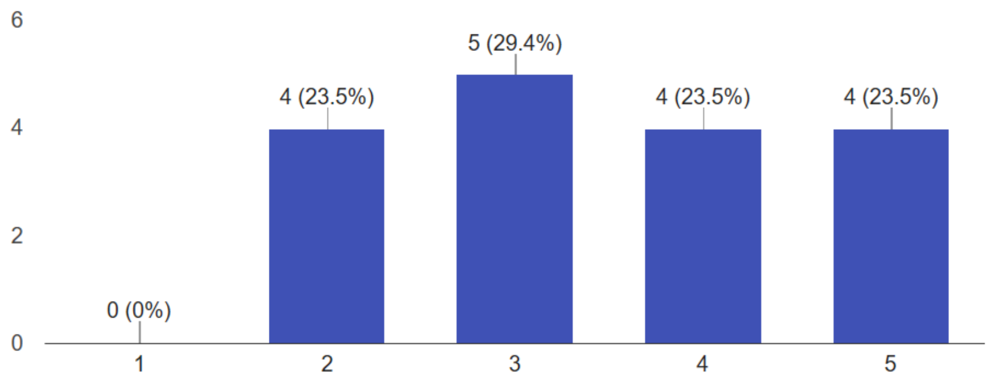
10 responses

We use to register as much data as possible, including climatic conditions, infrastructure conditions, etc.
Level of attentiveness of drivers
Scenario information from vehicle/infrastrucutre sensors
Driver-looking cameras
weather data
Any Othello available data is interesting, nur currently this question is a Research topic from is.
Infrastructure conditions
all possible information would help
Even lighting conditions for video analysis, partly controlled environments.
debriefing from drivers

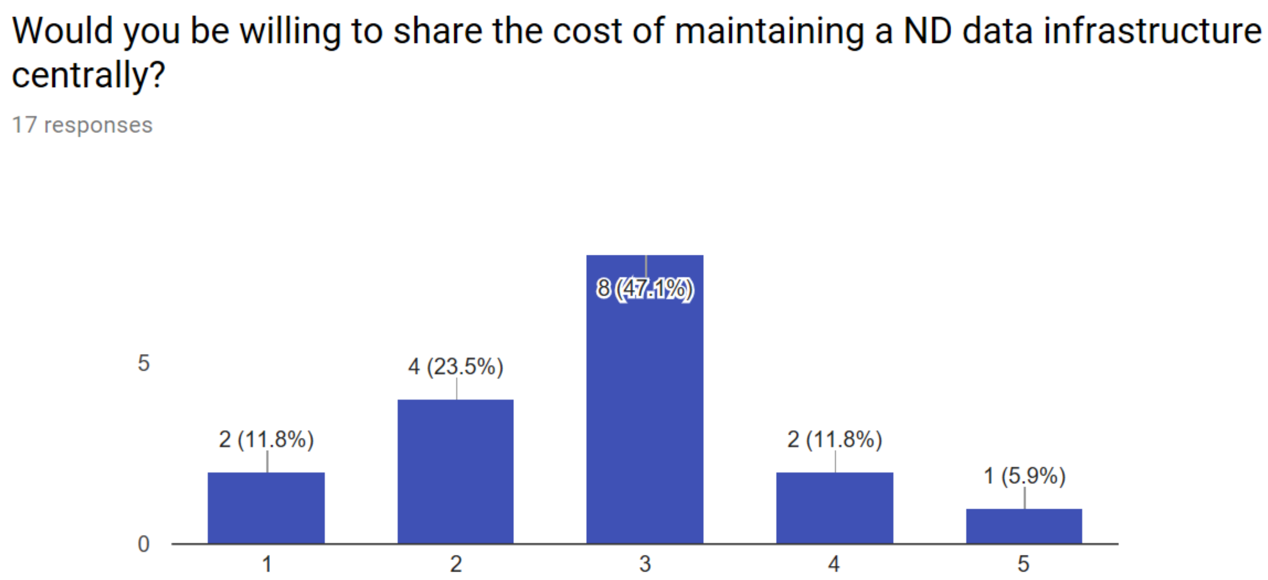
Interest to share ND data across parties

If you collect ND data, would you be interested to share it so you can access a larger pool of ND data – to make comparison/baselines?

17 responses



“not interested” versus “very interested”



"not willing" versus "very willing"

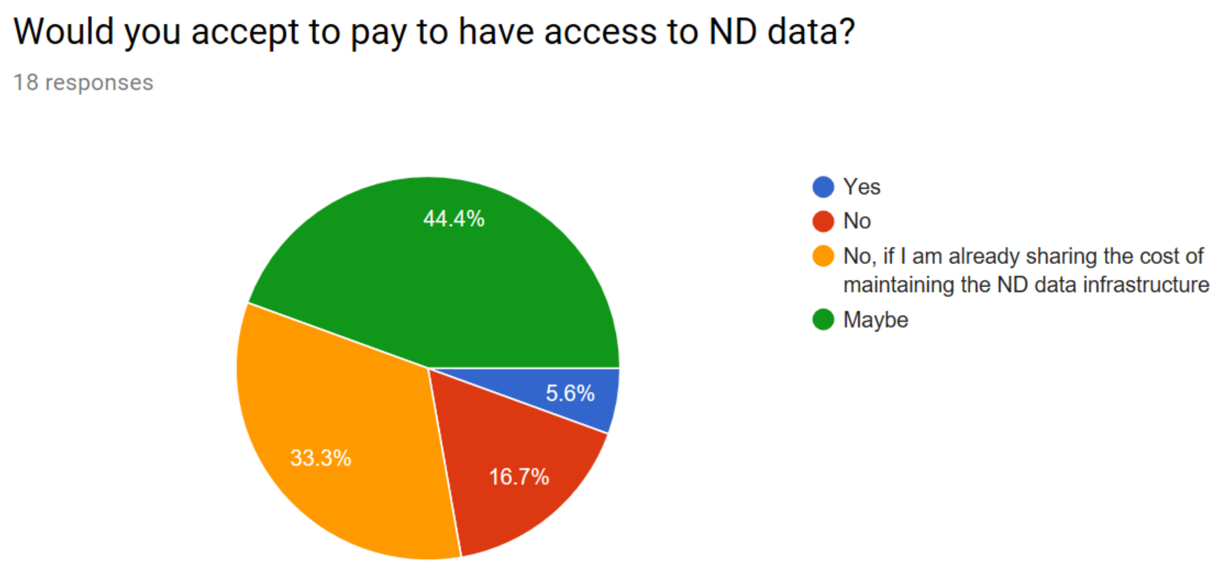


Figure 9 Questionnaire results (for intepretation see previous paragraph 4.1)

4.3 Business model for collecting data

Over the past years, the number of organisations gathering road data has been dramatically increasing. The reasons for this boom in road data collection are the ease of collecting and sending large amount of data using consumer electronic devices. Dashcams, GOPRO, smartphone apps, and the likes, have been sold in millions of units. The main purpose is not research; by far, the main reason is that it helps the owner to have first hand evidence in case of a car accident. It is perfect for transport companies, taxis, bus, vans & trucks, to monitor their rolling stock. Insurance have also made many attempts to link third-party data collecting devices to their pay-as-you-drive insurance policies which also helps to fight fraud. Some of them are using OBDII dongles to collect additional vehicle data. Moreover, most of the new models of vehicles have large amount of memory to collect considerable amount of data from on-board sensors.

So why does it work so well to collect data for businesses and private persons while researchers are struggling to equip a couple of hundreds of vehicles for research purpose. The answer is in the approach.

The first lesson we need to learn is to bundle data collection with direct return of value like a service. As an example, you would like, as a researcher, want to research whatever behaviour of commercial vehicles in a city, and, instead as a service provider, you equip fleets of taxis or vans with OBDII dongle and an online eco-driving app giving advices to the fleet owner and the drivers. This is what most smartphone applications do – so why wouldn't the researcher community do it as well.

The second lesson we should learn is to be happy with what data is already being collected and work on making it accessible. Indeed, the research community often thinks of ND data collection as an experience in itself. The UDRIVE community chose to equip vehicles with up to eight cameras because this was not done so far. This may be the wrong approach. For a fraction of the money and time spent, off-the-shelf data recorders could have been used to record ND data from many more vehicles. In addition, cooperation with commercial organisation operating data collection may have resulted in a huge access to research data potentially triggering long term alliance between the interested parties.

Last, it is important to work with the vehicle manufacturers to trigger long term cooperation while relieving them from the burden of collecting sensitive data. The prospects of a neutral non-profit organisation gathering data from the vehicles but also using this data for product research at the service of the vehicle manufacturer or their supplier may become a great answer to the new General Data Protection Regulation.

To conclude, ND data collection does not need to be a long and painful research process but could be very well embedded, as an integral part, in the product design being a vehicle, a dashcam, an app with a dongle. Changing this mindset may change the future of ND data research.

5 Continued and open access to UDRIVE data after the project

During the UDRIVE project, a considerable amount of data has been collected. From the start, the UDRIVE consortium has planned to open-up the data for re-use after the project. The main motivations to keep the data available and secure and share the coverage of the related costs are:

- The data collected is an asset to the whole research community for future road transport research
- Project partners have an interest to maintain access to the data for future research

The UDRIVE dataset made available will include:

- the data collected in the vehicles
- map data and mobilEye data used in the project
- common annotations
- derived measures

A possible re-use of the data can be for developing ADAS functions, virtual testing, modelling and behaviour based safety programmes as described in previous chapters of this deliverable. Currently, the work group within UDRIVE aiming to realise this continued access of the data after UDRIVE faces some challenges to make the UDRIVE data available. Main challenges are: 1) the costs to host the data and keep it available 2) financial model for continued access, and 3) privacy barriers (video data of faces etc.).

When forming the procedures and financial model, it is important to take the following pre-requisites into account which has been settled earlier in the Grant Agreement and the Consortium Agreement:

- All UDRIVE partners own the data
    - Each UDRIVE partner (see Appendix A for UDRIVE partners) share the intellectual property right to the collected data
    - The UDRIVE data may be used by any of the UDRIVE partners on a royalty-free basis without prior agreement of the other partners, though limited by that the partners may not grant licenses to the data to third parties.
- Data will be made available after the project if the financial costs are covered.
- Partners will be able to download the data during three years after the project.
- Any handling and use of the data must follow the Data Protection Concept (DPC), also if downloading the data after the project.
- Only UDRIVE partners can get remote access to video
- Third parties can only get remote access to non-personal data
- Third parties can go to partners for video access
- The data analysis tool will be available after the project (certain activities such as additional enhancements will be paid per hour)
- A lighter version of the tool will be available to all third parties.
- Data always stays in a secure storage except after authorized extractions and if a partner download the data, where in both cases the data is encrypted.
- Projects involving third parties is to be reported to the EC
- Collected Data may only be used for research purposes so this excludes commercial exploitation of the data for business purposes

5.1 Costs to host the data

There are fixed and variable costs that need to be covered by the financial model. Fixed costs are typically the costs for the database hosting and maintenance, the infrastructure IT and administrative management. These costs are the basis for the calculation of the annual fee. Variable costs are directly related to the use of the data, such as the access set up, number of users, storage, data extraction and related supporting services.

5.2 Financial model for continued access

The main objectives of the post UDRIVE data access model are to:

- Maintain the database and ensure data access for UDRIVE partners for at least 6months with an option of 6 months
- Cover the fixed costs of keeping the data available and lower the financial risk
- Allow to enhance the database to attract new users and thus build a stable community of users that would allow to continue the database beyond the first year

Two different financial models were proposed:

1) Member based model in which first UDRIVE partners become members and additionally third parties can become members
2) A project based model that aims at possible coverage from external projects of the costs. Each project within has to pay the same amount for the access of the data.

5.3 Business model for (re-)using ND data

FOT-Net Data project has described a series of six financial models (Gellerman et al., 2017) for the re-use of FOT and ND collected data by interested parties. Table 1 shows the different options. The first two (A and B) are based on addition public funding after the end of the data collection. Original project-based funding are reflected in the models C–E (not possible in the current project), and models F–H charge the costs on the end user e.g. through membership fees or licenses.

Table 1: FOT-Net Data financial models (Gellerman et al., 2017)

Financial model	Example	Costs for re-user
A – Organisations' core activity	Public funding directed to preservation activities, e.g. university digital library	Non-profit price
B – e-Infrastructures	Publicly funded supercomputing centres, additional services have a price	Free (basic services)
C – Archival included in project budget	Research team storing data in archival services	Free or non-profit price
D – Project extension	Multi-million projects apply for extensions to promote their data	Free or non-profit price, even calls for analysis proposals
E – New project funding	Research projects using previous datasets	Commercial price
F – Established network	Accident data collection and sharing	Different levels of memberships and fees
G – Analysis services	Notable data owners offering services	Commercial price
H – Data integrators	Road operators putting together information services	Commercial price

Out of which only one would allow to re-use the shared data with enough scalability to open it up to industry research: An “established network” in which all parties participate financially to the cost of maintaining the ND data and the tools that go with it. If this model fails due to the lack of volunteering partners, the second best choice would be to continue exploiting the ND data as an on-demand consulting service with little opportunity for economies of scale and therefore relatively high consulting costs. Other example of a data sharing project is the Research Data Exchange in the US. The sharing framework is maintained by the US DoT as a public resource for the research community.

After more than a year of discussions, the UDRIVE consortium seems to opt for a mix of of “F” and “G” options. A smaller group of research organisation with extensive data analysis competence are gathering the necessary budget in order to commonly maintain the data and the analysis tools. Each participating organisation will be free to monetise the use of the ND data at their own discretion through bilateral contracts with commercial organisation. The ND data can be mined remotely using authorised access. This solves the privacy issue: the group of organisations keeps full control on the privately sensitive data through strict data protection procedures. At the same, time it can still access private data for any research studies ordered by a customer. However, this solution only solves the problem of the UDRIVE ND data collected during the project, which brings the question of the business model for collecting more data in the future.

6 Conclusions

Regardless of technical domain, where functions are being developed which should interact with a human in one way of another, it is crucial to have explicit understanding of real problems or issues experienced by users in real environments, that is, have a user centred design process (ISO 9241-210).

6.1 Main findings

C*hapter two* described how ND data can be used by the vehicle manufacturing industry to facilitate the development of driver support functions

For function development (ranging from passive to more advanced driver-assistance systems (ADAS) as well as higher level of automation functions), capturing both normal driving as well as accidents and incidents through collected naturalistic driving data (NDD) can be used in combination with statistical crash data. Examples of where function developers can have a strong need for naturalistic driving data were given e.g. for basic tuning of the automated driving functions. NDD can be used in order to *define target scenarios* and to *select appropriate countermeasures and for sketching use cases* in early development phases. Information captured in NDD can serve as input when *developing proper driver-, system-, vehicle- and environmental models* for pre-crash and crash simulations *evaluate the safety performance of a specific driver support function.*

Further more, chapter two described simulation tools that could benefit for virtual testing. For example, to assess the benefits of an ADAS it's necessary to know how drivers behave in specific situations and how drivers react to the interventions by their vehicle. ND data (with or without systems) can be used to provide the relevant data to develop, test and validate the behaviour models. PEARS network and OPENPASS are initiatives that harmonise simulation tools and create a new software framework for simulation and evaluation of active safety and different types of automated functions in an integrated manner.

Chapter 3 answered the question how ND data can be used in behaviour-based safety programmes. In order to shape custom-made behaviour-based driver coaching, in-depth behavioural knowledge is required. A major part of this in-depth knowledge is to comprehend the mechanisms of driver behaviour. One example of the reason why it is necessary to comprehend specific behaviour is to successfully avoid a precipitating event, in other words understand behaviour in safety critical events that *do not* lead to a crash event (Wege, 2013). Thus far, the results retrieved from the analysis of the short time-span before a precipitating event has been often used for understanding crash causation (e.g. Victor et al., 2015) and less for tailormade driver coaching and training. Two specific use cases showing the value of ND data for enhancing coaching strategies for driver coaching programmes are coaching teen drivers and coaching commercial truck drivers. Driver coaching can be aimed at safety, fuel consumption, vehicle care, driver health, customer communication, stress management and other driving behaviours. For successful safety programs and coaching programs, it is necessary to track reliable ND data to provide timely and effective feedback to the driver. The intended results of coaching programs are the formation of new habits. If successful, this can be accompanied by a change in attitude, feelings, stress level, and self-perceived performance on the coaching targets.

In *chapter 4* a series of potentially interested companies who could benefit from ND studies have been consulted. The questionnaire received nineteen responses some of which were followed up by phone conversations. Additional phone conversations took place in order to complete the industry representativeness of the sample.

There was a highest interest expressed for in-vehicle data from CAN, radar and cameras (outside and driver views). There is a growing interest to access (historic) probe data, which is considered to be highly valuable to understand traffic bottlenecks or mobility patterns. The potential is perceived by the parties but they see so many legal and practical hurdles to access such data that it easily gives up along the way. A recurrent issue mentioned by the potential ND data users is their lack of expertise to analyse the data. The community at large would welcome any improvements to access collected ND data but the lack of expertise seem to remain the greatest issue.

For the ones who have ND data analysis expertise, their main plea is to have a one-stop European approach where many different data sets can be shared with economies of scale on the data infrastructure and required computing power. If a data infrastructure would exist, a give and take model seemed to be the most likely: the parties expressed their interest to share data at the condition that they can access other data sets. On the willingness to pay, most of the respondent could not express themselves at this stage; 50% remained positive to pay for the access to the data whereas a third preferred an option where they participate commonly to the cost guaranteeing the access to the data. Still, the impression during interviews was that the majority preferred the option of paying for what they ask for rather than having to develop all skills to analyse the data.

The chapter concludes with three lessons learned:

1) Bundle data collection with direct return of value like a service. This is what most smartphone applications do – so why wouldn't the researcher community do it as well?
2) Data is already being collected by companies. Explore cooperation with commercial organisations that are operating on data collection which can result in a huge access to research data potentially triggering long term alliance between the interested parties.
3) Work with the vehicle manufacturers to trigger long term cooperation while relieving them from the burden of collecting sensitive data. The prospects of a neutral non-profit organisation gathering data from the vehicles but also using this data for product research at the service of the vehicle manufacturer or their supplier may become a great answer to the new General Data Protection Regulation.

Chapter 5 describes the possibilities for continued and open access to UDRIVE data after the project Main challenges are: 1) the costs to host the data and keep it available 2) financial model for continued access, and 3) privacy barriers (video data of faces etc.). FOT-Net Data project has described a series of six financial models for the re-use of FOT and ND collected data by interested parties Two different financial models were proposed for UDRIVE. A member-based model in which first UDRIVE partners become members and additionally third parties can become members. A project-based model that aims at possible coverage from external projects of the costs. Each project within has to pay the same amount for the access of the data. The ND data can be mined remotely using authorised access. This solves the privacy issue: the group of organisations keeps full control on the privately sensitive data through strict data protection procedures. At the same time it can still access private data for any research studies ordered by a customer. However, this solution only solves the problem of the UDRIVE ND data collected during the project, which brings the question of the business model for collecting more data in the future.

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List of abbreviations

ADAS	Advanced Driver Assistance Systems
ND	Naturalistic Driving
NDD	Naturalistic Driving Data
NFOT	Naturalistic Field Operational Trial

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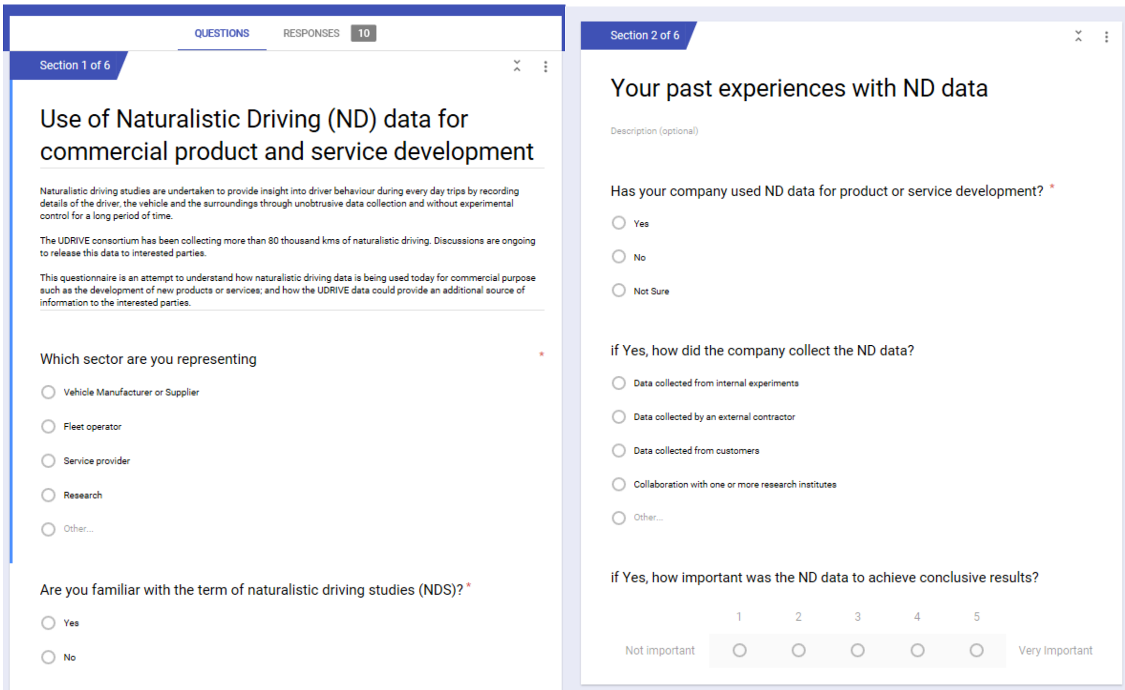
Appendix A Business model questionnaire

Link to questionnaire: https://goo.gl/forms/CVGIFHPReJ4iSfs23

Nineteen people filled out the online questionnaire (Fig 1.).



QUESTIONS RESPONSES 10

Section 1 of 6

Use of Naturalistic Driving (ND) data for commercial product and service development

Naturalistic driving studies are undertaken to provide insight into driver behaviour during every day trips by recording details of the driver, the vehicle and the surroundings through unobtrusive data collection and without experimental control for a long period of time.

The UDRIVE consortium has been collecting more than 80 thousand kms of naturalistic driving. Discussions are ongoing to release this data to interested parties.

This questionnaire is an attempt to understand how naturalistic driving data is being used today for commercial purpose such as the development of new products or services; and how the UDRIVE data could provide an additional source of information to the interested parties.

Which sector are you representing *

- Vehicle Manufacturer or Supplier
- Fleet operator
- Service provider
- Research
- Other...

Are you familiar with the term of naturalistic driving studies (NDS)? *

- Yes
- No

Section 2 of 6

Your past experiences with ND data

Description (optional)

Has your company used ND data for product or service development? *

- Yes
- No
- Not Sure

if Yes, how did the company collect the ND data?

- Data collected from internal experiments
- Data collected by an external contractor
- Data collected from customers
- Collaboration with one or more research institutes
- Other...

if Yes, how important was the ND data to achieve conclusive results?

	1	2	3	4	5	
Not important	○	○	○	○	○	Very Important

Fig.1. Screenshots questionnaire