HAL4SDV

Systems Safety Security Software

Hardware Abstraction Layer for a European Software Defined Vehicle Approach

D5.6 Driver behavioral analyses report

VSB-TUO

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Table of contents

List of figures

List of tables

Abbreviations

BB	Building Block
CD	Continuous Delivery
CI	Continuous Integration
CT	Continuous Testing
CCAM	Cooperative, Connected and Automated Mobility
DDS	Data Distribution Service
EC	European Commission
ECU	Electronic Control Unit
EMF	Eclipse Modeling Framework
EU	European Union
HAL	Hardware Abstraction Layer
HPC	High-Performance Computer
IPR	Intellectual Property Right
OS	Operating System
OTA	Over The Air
RAG	Retrieval Augmented Generation
SDV	Software Defined Vehicle
SDVoF	Software Defined Vehicle of Future
SoC	System-on-a-Chip
SoP	Start of Production
SotA	State of the Art
SOA	Service Oriented Architecture
SW	Software
TA	Transversal Activity
TRL	Technology Readiness Level
UWB	Ultra Wide Band
VSS	Vehicle Signal Specification
WP	Work Package

Refer also to Full Project Proposal § 5. ABBREVIATIONS LIST [4]

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1 Summary

The Deliverable 5.6 (D5.6) entitled "Driver behavioral analyses report"; e.g. the ability of the driver to take longitudinal and lateral control over time provides a platform for joint consortia use both within the framework of further project solutions and for the purposes of development, research and education in the segment of driver reaction time analyses in a time-dependent manner. The platform for data collection and operational signals, including camera and radar data (UWB), was developed with the implementation of SDV principles (zonal E/E architecture) for driver behavioral analysis and is intended for comprehensive collection and evaluation of bio-signals in situations of taking over control from the automated SAE L3 and L4 modes to manual vehicle control.

It focuses on the critical moment of the so-called take-over request (TOR), when the driver is asked to take control of the vehicle again, and analyzes his physiological and cognitive readiness to perform this activity safely. The platform integrates sensors for measuring heart rate and its variability, electrodermal activity, eye movement and gaze tracking, or EEG, and complements them with analysis of facial expressions, reaction time, and the quality of first control interventions. This allows for a detailed assessment of the level of alertness, stress level, cognitive load, and situational orientation ability before and during taking control.

Moreover, this document describes the platform architecture and design as well as description of datasets processing.

The categorization of appropriate parameters of operational dynamic and state quantities of the vehicle is essential for further data management and annotation. Likewise, knowledge of the technical properties of sensory systems for monitoring bio-signals that can be monitored in the driver of experimental vehicles with a similar setup developed within this project is essential. Equally important is knowledge of the appropriate approach (e.g. scenario selection) to obtain relevant datasets for further use in determining reaction times, human control latencies and latencies of mechatronic and mechanical parts of systems.

The knowledge obtained can be used in determining requirements for the creation of SDV applications for CCAM.

This document is structured as follows: In chapter 2 an overview of the developed experimental platform. This includes experimental vehicle description, chapter 3 goes into detail on selected sensors and reasons for their applications. Chapters 4 give a description of dataset recording and data/signal processing with connection of GitHub project - https://github.com/mobility-lab-vsb/driver-behavioral-dataset (especially established for this project). The activities related to Driver Behavioral Analysis are subject to assessment by the Ethics Committee for Biomedical Research, what is described within chapter 4.4.

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2 Experimental Platform for Driver Behavioral Analyses

In this chapter will be described how the on-board experiment platform is designed and constructed.

2.1 Introduction

D5.6 was implemented using D5.7 – "Experimental & demonstration vehicle with partial elements of HAL4SDV platform for CCAM tasks" (planned full completion 36th month/M36; collaboration: VŠB-TUO, NXP CZ, NXP DE, NXP NL, Mercedes-Benz, Aumovio, ZF). This is an experimental and demonstration vehicle with partial elements of the HAL4SDV platform. Thanks to its new architecture, it is also used within the project for the implementation of assistance systems and for CCAM tasks. The vehicle provides a basic platform for SDV assistance and CCAM applications respecting SDV requirements (one of them will be the Follow the Vehicle assistance system and the other the "Cabin Child Detection" application). The development is carried out on the Škoda Enyaq Coupe vehicle (OEM MEB platforms; VW group). Specifically, the implementation with a platform of several HPCs, including the Car Over-Ride gateway. Within the HPC, this involves the development and implementation of the central HPC, IVI HPC and ADAS HPC.

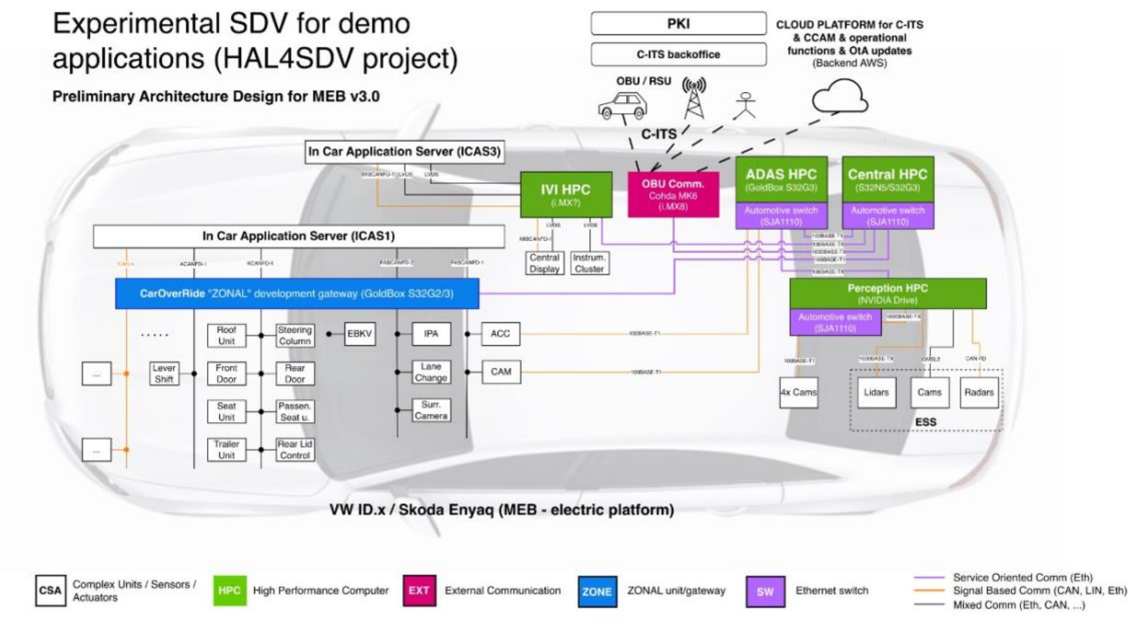

Figure 1 High-level architecture of the experimental vehicle Škoda Enyaq, the development of which is being carried out by the VŠB-TUO team and with partners support

This deliverable focuses on the platform, using external sensor elements and a data logger, provides objective data on the latency of response to a challenge, the accuracy and stability of the first steering inputs, as well as the subsequent stabilization of the driving trajectory. It can be integrated into driving simulators and real test vehicles, which allows scenario testing to be carried out in both normal and extreme operating conditions. The result is a quantifiable description of the driver's performance when switching between automated and manual modes, which is essential for the design of vehicle safety concepts.

The platform is a suitable tool for supporting Functional Safety processes according to ISO 26262 and related standards, as it allows validating assumptions about the driver's ability to take over control within a defined time frame and provides data for creating safety arguments within the Safety Case. The data obtained can be used when designing HMI requirements, defining safety boundaries between automated and manual modes, and assessing risks associated with the human factor.

At the same time, the platform supports the implementation of Fail-Safe and Fail-Operational strategies. It allows to identify situations where the driver is not able to react safely and initiate a Minimum Risk Maneuver. Within the fail-operational approach, it then provides the basis for adaptive decision-making of the system based on the current state of the driver, for example by adjusting warning strategies, extending the autonomous mode or escalating the calls to take over the control. Thanks to the possibility of long-term data collection and analysis, it is also possible to create predictive models of driver readiness, which further increase the safety and reliability of automated driving systems.

2.2 On-Board Measuring Setup

Below is a basic block diagram of the concept of the developed measurement platform for collecting data sets for the purpose of the created "Driver Behavior Analysis Report", e.g. the driver's ability to monitor the vehicle's behavior in the transverse and longitudinal directions during the driving time.

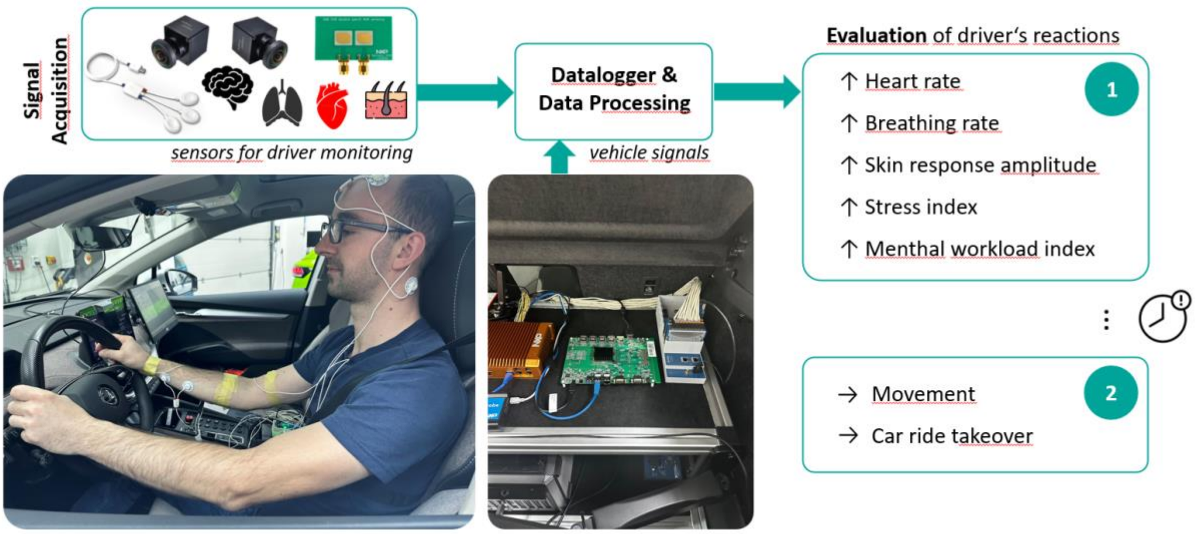

Figure 2 Basic overview diagram with picture of the on-board measuring setup in the experimental vehicle with the datalogger

Figure 2 The figure shows a basic block diagram that presents the connection of two data sources. On the one hand, bio-signals and physical manifestations of the driver's behaviour are recorded using a UWB radar or camera, and on the other hand, vehicle operating signals are logged (dynamic variables documenting vehicle behaviour and state variables of vehicle systems).

Bio-signals are manifestations of a living organism that provide insight into complex processes occurring in the body. These signals can be electrical (e.g. cell activity), mechanical (e.g. blood pressure) or chemical (e.g. enzyme composition). Thanks to modern technologies, these signals can be captured and analysed, which provides valuable information about the state of health. The development and improvement of sensors and analytical methods open up new possibilities in the field of medical diagnostics and monitoring of the health of patients. In transport, the detection of bio-signals is important both from a safety point of view and from a development point of view. Monitoring bio-signals, for safety reasons, mainly concerns the detection of fatigue and subsequent driver notification. In development, monitoring biological signals is important, especially for monitoring human behaviour, when using assistance systems, or when driving with new technology in the form of automated driving.

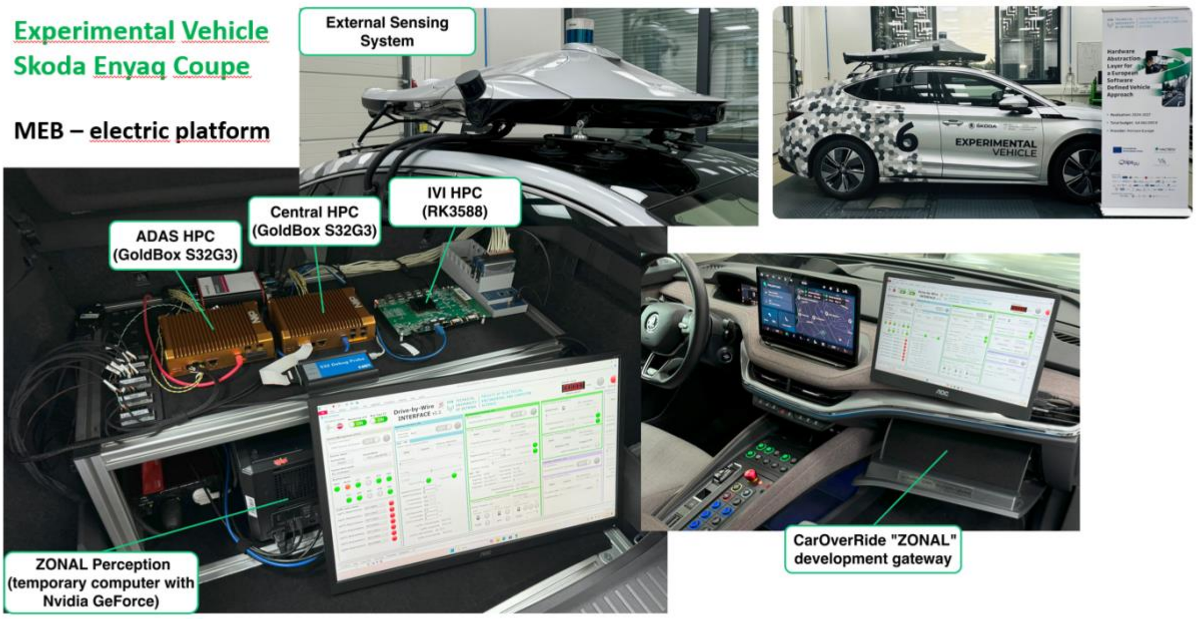

Figure 3 Basic overview diagram with picture of the experimental vehicle with datalogger.

Figure 2 shows the experimental vehicle with physical implementation of development “SDV” Zonal architecture (including HPCs, IVI and Car Override Zonal Gateway) and an additional onboard system for acquiring vehicle operating signals, driver bio-signals and other signals representing the driver's dynamic behaviour. Vehicle has implemented also multimodal perception sensing system as reference sensing system to collect image data and 3D object information (surround data collected around the vehicle under test). Multimodal perception sensing system is implemented just for case of additional requirements for reference data from R&D partners or academical scientific community. Not used for our first dataset published in GitHUB for M24 report.

Figure 3 provides detail overview how was mentioned “Driver behavioral measuring setup” implemented do the Experimental SDV (D5.7). Beside others, there you can see the communication between the systems in frame of Experimental SDV. Central HPC is responsible for microphone audio signal processing and also for communication with the cloud, and Kuksa Databroker will also run here. We use Kuksa for communication between

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the Linux part of the systems, whose signals we are able to forward to the realtime M7 application using NXP IPCF. For real-time vehicle control communication is used SOME/IP.

Deliverable 5.6 till M24 is not use for any SDV applications. However, it's possible on the of base of partners requirements during last year of solving.

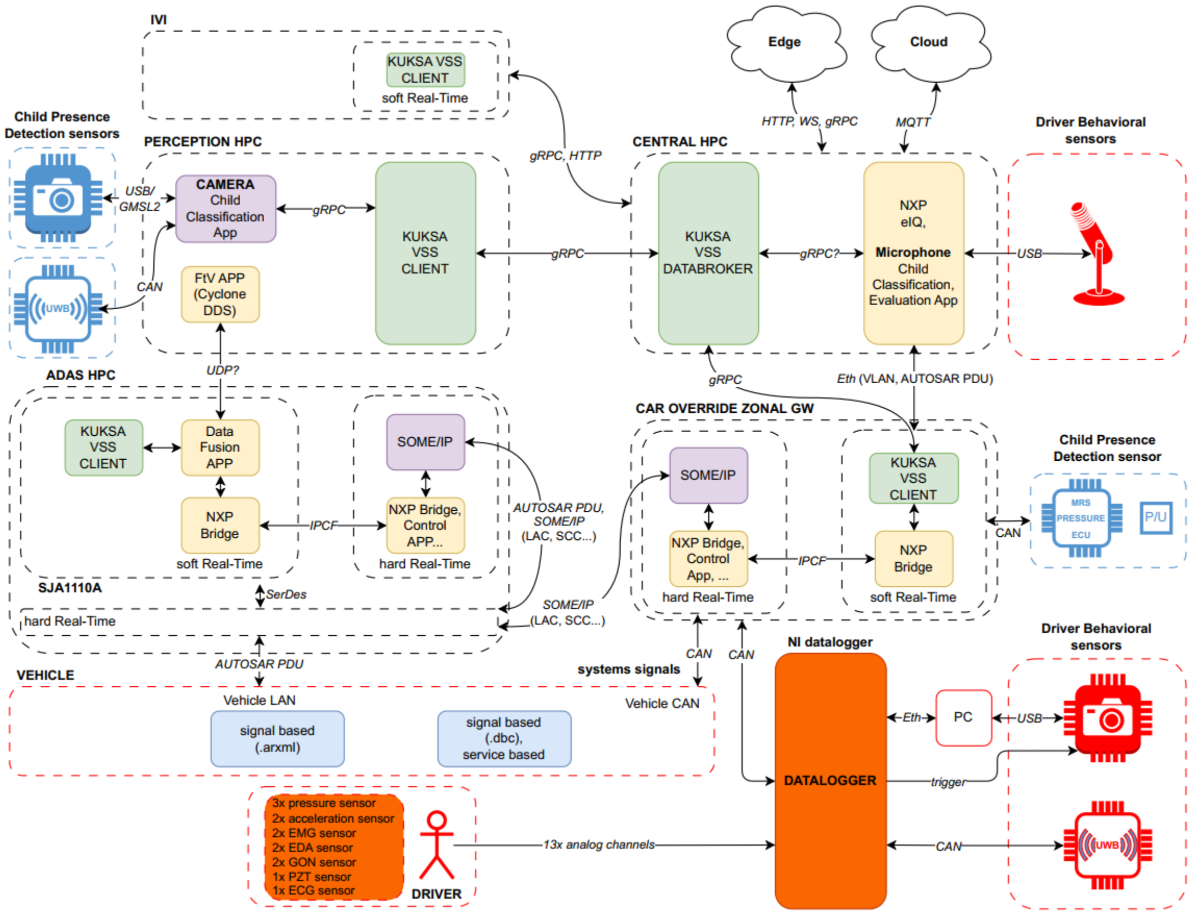

Figure 4 Detail connection diagram of Multimodal sensing and datalogging platform for driver behavioral analysis

On-Board driver behavioral measuring setup consists of:

- NI datalogger (NI CAN Breakout Box; NI-9220 module, NI-9860 module, NI-9263 module; NI9223 with BNC module),
- measuring personal computer for camera (image processing),
- set of sensors, please see table 1,
- datalogger SW configuration,
- Car Override Zonal GW firmware for vehicle signal providing (including .dbc file).

2.3 Sensing System Overview

For the behavioral analysis of drivers, we developed a measurement setup integrated into the vehicle Škoda Enyaq Coupe. This system enables comprehensive acquisition of bio-signals and micro-movements of the driver under real driving conditions, with an emphasis on multimodal data acquisition and synchronization.

For bio-signal monitoring and body capturing, sensors from PLUX were selected due to their accuracy, non-invasiveness, and compatibility with mobile measurement systems. The specific sensor configuration was designed to capture both physiological responses and motor behaviour of the driver:

1. **Accelerometers (2× ACC, one per hand)** were used to capture both fine and dynamic movements of the upper limbs, particularly interactions with the steering wheel. They enable quantification of micro-movements, tremor, and changes in motor behaviour under varying workload conditions.
2. **ECG sensor (1x)** was selected for continuous monitoring of cardiac activity. It provides key indicators of the autonomic nervous system, such as heart rate and heart rate variability (HRV), which are sensitive to stress, cognitive load, and emotional state.
3. **EMG sensors (2×, arm muscles)** allow monitoring of muscle activation, especially during steering tasks. These signals are essential for identifying physical strain, fatigue, and changes in motor control strategies.
4. **Piezo-Electric Respiration Sensor / Respiratory belt (PZT)** was included to measure breathing activity, which is closely related to psychophysiological state. Variations in respiration rate and amplitude provide complementary information to cardiovascular parameters.
5. **EDA sensors (Electrodermal Activity Sensor)** were used to measure skin conductivity (between fingers). Sensor is capable of accurately measuring the electrical properties of the skin which changes. These changes are caused by alterations in sweat secretion and sweat gland activity as a result of changing sympathetic nervous system activity. The low-noise signal conditioning and amplification circuit design provide optimal performance in the detection of even the feeblest electrodermal skin response events.
6. **Goniometers (2×)** are used for precise measurement of joint angles (e.g., wrist or fingers) and complement accelerometer data. This redundancy improves motion reconstruction robustness and supports data validation.

In addition to contact-based biosensors, non-contact and environmental sensing technologies were also employed:

7. **UWB radar (1x)** was implemented for contactless detection of body micro-movements, including subtle postural changes and respiration-related motion. Its key advantage lies in reliable sensing under limited visibility and without requiring direct contact with the subject.

   Ultra-Wideband (UWB) technology can be used not only for wireless communication but also for radar-based sensing applications. In this work, UWB is utilized specifically as a radar system, where short electromagnetic pulses are transmitted and their reflections from the environment are analysed. Due to its very wide bandwidth, UWB enables high temporal resolution, which is essential for precise detection of object distance and movement.

   The operating principle of a UWB radar is based on transmitting short pulses and evaluating the resulting Channel Impulse Response (CIR). This response contains information about signal propagation delays and reflections from objects in the environment. By analysing changes in the CIR over time, it is possible to detect motion, even at a very small scale, such as micro-movements caused by human breathing. One of the main advantages of UWB radar is its ability to achieve high spatial resolution and distinguish between direct and reflected signal paths, making it robust in environments with significant multipath propagation. Additionally, UWB operates with low transmission power, which minimizes interference with other systems and makes it suitable for continuous sensing applications.

UWB radar was chosen in this work primarily due to its capability to detect subtle variations in the environment without requiring direct contact or line-of-sight conditions typical for optical systems. By applying signal processing techniques such as filtering and frequency-domain analysis, it is possible to extract physiological parameters, such as breathing rate, from the measured CIR data. Due to these characteristics, UWB radar is increasingly used in applications such as presence detection, vital sign monitoring, automotive sensing, and indoor environment analysis. In this work, it is specifically applied to breathing detection based on the analysis of temporal variations in the CIR signal.

8. **Camera (1x)** was used for visual body capturing, enabling analysis of posture, body position, and gestures. The video stream also serves as a reference modality for validation of other sensor data.
9. **Pressure sensors (3x seat-integrated)** were used to detect seat occupancy and pressure distribution. They enable monitoring of micro-movements, posture shifts, and indicators of discomfort or fatigue.
10. **Audio microphone (1x)** a USB-C lavalier microphone was included to capture the driver’s speech and vocal expressions. Its omnidirectional pickup pattern ensures consistent audio acquisition regardless of head orientation, while the clip-on design enables unobtrusive, hands-free recording. This modality provides valuable information about cognitive load, stress, and driver interaction through voice analysis. Also for driver co-annotation comments.

The overall system is designed as a multimodal measurement platform, where individual sensors provide complementary information. By combining physiological, kinematic, and spatial data, the system enables a detailed understanding of driver behaviour, including the identification of stress, fatigue, cognitive load, and changes in motor performance during driving.

Table 1 Used sensors and their description

Sensor type	Basic Description	WEB Link	Technical Parameters
Accelerometer (ACC)	3-axis accelerometer for hand movement (each hand separately)	https://www.pluxbiosignals.com/products/accelerometer-acc	3-axis (X,Y,Z); range ±2g to ±16g; sampling up to ~1000 Hz; motion dynamics detection
ECG sensor (ECG1-2477)	Measures electrical activity of the heart (clavicle–abdomen placement)	https://www.pluxbiosignals.com/products/electrocardiography-ecg-sensor-1	1-channel ECG; range ±1.5 mV; bandwidth ~0.5–40 Hz; HR and HRV analysis
EMG sensor	Measures muscle activity (e.g., arm muscles)	https://www.pluxbiosignals.com/products/electromyography-emg	Range ±1.5 mV; bandwidth ~20–450 Hz; gain ~1000x; muscle activation analysis

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PZT sensor (Respiration)	Respiratory belt measuring chest expansion	https://www.pluxbiosignals.com/products/respiration-pzt	Piezoelectric sensor; breathing rate detection; low frequency ~0.1–1 Hz
EDA sensor	Skin conductance measurement (typically between fingers)	https://www.pluxbiosignals.com/products/electrodermal-activity-eda-sensor-1	Range ~0–25 µS; DC measurement; bandwidth ~0–5 Hz; stress/arousal indicator
Goniometer (GON)	Joint angle measurement (e.g., fingers, wrist)	https://www.pluxbiosignals.com/products/goniometer-gon	Angle measurement up to ±180°; analog output; suitable for kinematics
UWB radar (NXP LID2580 / NCJ29D6)	Contactless sensing of body movements (both hands and head) and micro-body movements (respiratory movements) and the presence of a person in the vehicle cabin	NCJ29D6 Customer Evaluation Board (LID2580) | NXP Semiconductors	UWB (Ultra-Wideband) transceiver with radar function; IEEE 802.15.4z compatible; combination of ranging + radar; detection of motion, distance and angle of arrival of the signal (AoA); support for multiple UWB channels (CH5, CH6, CH8, CH9); high immunity to interference; integrated control (Arm Cortex); CAN, USB, UART interfaces
Camera (Basler daA1920-160uc)	Industrial RGB camera for body capturing, tracking driver posture, gestures and movements	Basler dart daA1920-160uc (S-Mount) | USB 3.0 Board Level Camera | Basler AG	CMOS sensor (Sony IMX392); resolution 1920 × 1200 px (~2.3 MP); frame rate up to 160 fps; global shutter; pixel size 3.45 µm; sensor format 1/2.3"; USB 3.0 interface; 8/12-bit depth; color camera
Pressure sensor (WIKA A-10 / OEM Automatic)	Pressure sensor to detect seat load and driver micro-movements through changes in pressure distribution	https://www.oemautomatic.cz/produkty/tlak-a-prutok/snimace-a-spinace/sn%C3%ADma%C4%8De-a-sp%C3%ADna%C4%8De-tlaku-a-diference-_-C30531/sn%C3%ADma%C4%8De-tlaku-a-talkov%C3%A9-diference-_-C30559/sn%C3%ADma%C4%8De-tlaku-a-10-_-P1825226	Range typ. 0–0.05 to 0–100 bar (depending on variant); output 0–10 V or 4–20 mA; power supply approx. 8–30 V DC; accuracy ~0.5 % of range; protection IP65; material stainless steel 316L; operating temperature approx. 0–80 °C; process connection G1/4
Microphone (USB-C Lavalier, ProSound 459PAM)	Lavalier microphone for capturing the driver's voice and acoustic expressions (e.g. speech, reactions, vocal load)	https://cpc.farnell.com/prosound/459pam/usb-c-lavalier-microphone/dp/PY32338	Omnidirectional characteristics; USB-C connection; cable length 2 m; high sensitivity for speech recording; integrated noise reduction + windscreen; plug & play compatibility with smartphones, PCs and data loggers

3 Rationale for Driver Behavioral Analyses

The increasing deployment of safety-relevant Software Defined Vehicle (SDV) applications within Cooperative, Connected and Automated Mobility (CCAM) environments further increases the need for detailed knowledge of driver behaviour and reaction capability.

Functions such as adaptive takeover management, cooperative manoeuvring, remote assistance, and fail-operational control strategies cannot be designed solely on the basis of fixed assumptions regarding driver readiness. Instead, they require reliable information about typical reaction times, intervention quality, and the influence of driver state on takeover performance. This is particularly important for SAE Level 3 automated driving, where the automated system may request that the driver resume control within a limited time interval. The availability of objective behavioral data therefore provides an essential basis for defining takeover timing, validating fault-tolerant time intervals, and ensuring that SDV-based CCAM applications can safely and robustly interact with the driver under real operating conditions.

The transition from SAE Level 2 to Level 3 and Level 4 automated driving fundamentally changes the role of the driver and introduces new safety challenges related to the transfer of control between the automated system and the human operator. While Level 2 systems still assume continuous driver supervision, practical experience shows that drivers frequently become disengaged, over-rely on the assistance functions, and are often unable to react appropriately in critical situations. At higher levels of automation, this issue becomes even more critical, as the driver is no longer expected to remain continuously involved in the control loop, yet must still be capable of safely resuming control when required.

For this reason, traditional safety approaches based on the assumption of an always-ready driver are no longer sufficient. The actual ability of a driver to perceive a hazard, make an appropriate decision, and regain stable vehicle control is highly dependent on the driver's current physical, cognitive, and situational state. Consequently, the safety of automated driving systems requires an objective and measurable assessment of driver readiness and takeover capability rather than relying solely on predefined assumptions.

This chapter therefore introduces a driver behavioral analysis platform designed to evaluate, in real time, the driver's readiness, reaction capability, and quality of intervention during the takeover process. By combining physiological, behavioral, and vehicle dynamics data, the platform enables a comprehensive assessment of the complete transition from automated to manual driving. In doing so, it provides a practical basis for validating the assumptions used in the design of automated driving functions and for determining whether the driver can safely re-enter the control loop within the available time budget. The chapter further explains how this platform supports the requirements of ISO 21959, ISO 26262, and ISO 21448. Particular attention is given to the decomposition of the takeover process into perception, cognition, action, and stabilization phases, the realistic evaluation of controllability and fault-tolerant time intervals, and the identification of risks arising from limitations in driver behaviour and situational awareness. Through this approach, the driver is no longer treated as an assumed component of the safety chain, but as a measurable and manageable element of the overall safety architecture of automated vehicles.

3.1 Motivation for Driver Behavioral Analyses

The transition from SAE Level 2 to Level 3 and Level 4 automated driving introduces a fundamental safety challenge related to the driver's reduced engagement and uncertain readiness to resume control. While L2 systems assume continuous driver involvement, real-

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world operation demonstrates frequent driver disengagement and over-reliance on assistance systems, leading to delayed or inappropriate reactions in critical situations. In higher automation levels, this issue becomes safety-critical, as the system can no longer rely on immediate driver fallback. The proposed driver behavioral analysis platform directly addresses this challenge by providing objective, real-time assessment of driver readiness, response capability, and control quality. This enables the replacement of assumption-based safety models with data-driven evaluation of human performance under realistic conditions.

From the perspective of **ISO 21959**, the platform operationalizes key concepts related to human performance in automated driving, specifically the decomposition of takeover into perception, cognition, and action phases. The platform enables measurement of each of these phases through synchronized behavioral, physiological, and vehicle data, thereby supporting the identification of delays in perception, decision-making, and control stabilization. This allows direct validation of human performance assumptions used in system design, particularly in takeover scenarios. In the context of **ISO 26262**, the platform provides critical input for the assessment of controllability within Hazard Analysis and Risk Assessment (HARA). Controllability is defined as the ability of the driver to avoid harm through timely and appropriate reaction; however, in practice, this capability is highly variable and dependent on driver state. The platform enables determination of driver reaction times, intervention quality, and stabilization performance, thereby supporting realistic classification of controllability levels and contributing to the definition of the fault-tolerant time interval. This is particularly relevant for high-ASIL systems, such as steer-by-wire, where incorrect assumptions about driver capability can lead to insufficient safety margins. With respect to **ISO 21448**, the platform addresses risks arising from system limitations in the absence of faults, particularly those related to human behavior. Real-world scenarios frequently involve correct system operation combined with inadequate driver response, for example due to distraction or reduced situational awareness. The platform enables identification and quantification of such scenarios by linking driver state with system behavior and environmental conditions. This supports the identification of triggering conditions and performance limitations required for SOTIF analysis.

The transition between automated and manual driving, highlighting the critical takeover phase bounded by the fault-tolerant time interval. During automated driving, the driver is outside the active control loop, while the system performs perception, decision-making, and actuation. Upon a take-over request, the driver must re-enter the loop through sequential phases of perception, decision, intervention, and stabilization. This transition is governed by constraints derived from **ISO 21959**, which defines the structure of human performance, **ISO 26262**, which requires definition of maximum handling time and controllability, and **ISO 21448**, which addresses risks related to driver misuse and performance limitations. This emphasizes that the fault-tolerant time interval must accommodate the full takeover process, while the actual driver readiness is variable and state-dependent. The proposed platform is positioned within this transition phase and provides direct measurement of driver state and response across all takeover stages. By capturing physiological, behavioral, and control inputs, it enables validation of whether the driver can safely re-enter the control loop within the available time budget. This allows identification of mismatches between assumed and actual driver capability, supports calibration of takeover timing, and enables the system to decide whether to transfer control or continue autonomous

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operation. In this way, the platform operationalizes the connection between human performance models and system-level safety requirements, transforming the driver from an assumed element into a measurable and controllable component of the overall safety architecture.

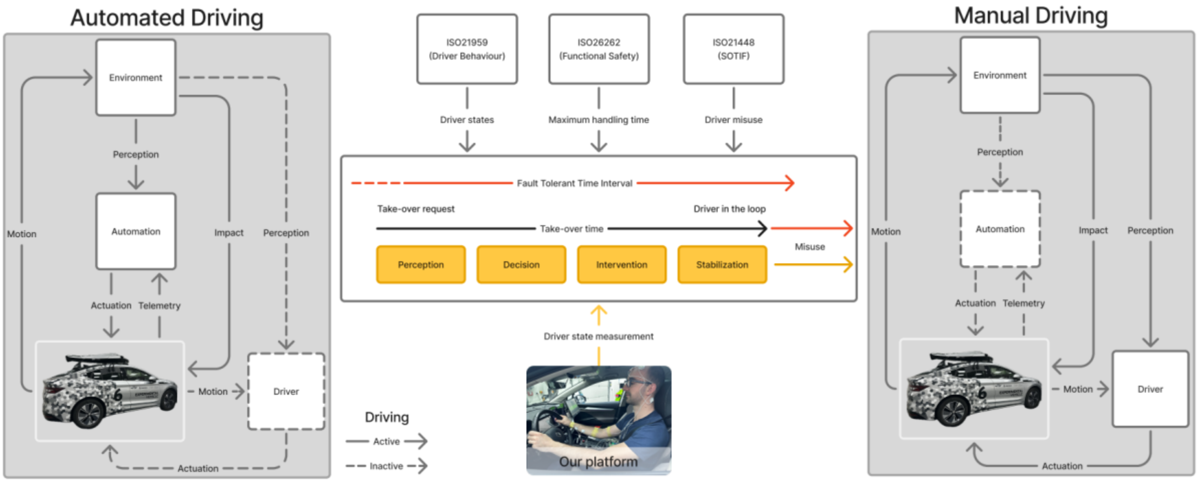

Figure 5 Block diagram of motivation in relevance with ISO 21959, ISO 26262 and ISO21448 standards

From a fail-operational system perspective, as demonstrated in steer-by-wire assessments, maintaining vehicle controllability during faults depends not only on system redundancy but also on driver perception and response. Experimental evidence shows that disturbances such as changes in steering feedback or lateral acceleration directly influence perceived controllability and driver reaction. The platform enables correlation of these vehicle dynamics with physiological and behavioral responses, allowing identification of thresholds beyond which safe driver intervention cannot be guaranteed.

In practical terms, the platform provides the following key contributions to system development and validation. It enables determination of realistic time budgets for safe takeover by comparing driver response capability with system fault-tolerant intervals. It supports calibration of takeover strategies by evaluating not only reaction time but also control quality and stabilization behaviour. It provides input for adaptive system strategies, where takeover requests, warnings, or minimum risk manoeuvres are adjusted based on the current driver state. It also enables continuous improvement through real-world data collection, supporting predictive models of driver readiness and long-term refinement of safety concepts. Also, possible implementation within a Software-Defined Vehicle architecture ensures portability and scalability across different platforms and use cases. This allows consistent evaluation of driver behaviour in diverse environments and accelerates the validation of automated driving functions under real-world conditions.

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4 Scientific Relevance for Driver Behavioral Analysis on the Platform

The following information provides a summary of a comprehensive view of related work from the scientific community. The content of this chapter is part of a forthcoming scientific article in an open access scientific journal with an impact factor. The scientific article will also include specific data based on the results of practical analyses on datasets available on the GitHub - https://github.com/mobility-lab-vsb/driver-behavioral-dataset (especially established for this project).

Analysis of driver's behaviour and cognitive workload during performing secondary tasks and non-driving-related tasks (NDRTs) were studied in many experimental scenarios. These are based on using autonomous driving [1], lane-keeping system (LKS) [2], or advanced driver assistance systems (ADAS) [3], particularly performed on driving simulators. In general, the measured parameters during these scenarios include driver's gazes and glances [4], cognitive workload [5], physiological features [6], or reaction and takeover times (TOTs) [7].

4.1 Takeover in Various Scenarios

Takeover time from autonomous to manual driving is an essential parameter for securing the safety of driver during autonomous mode failure or other unexpected events. The meta-analysis of TOTs from automated driving [1] showed a mean TOT from 0.69 sec to 19.79 sec depending on scenario, when the total mean value was found as 2.72 sec. If participants took over multiple times in a row or completed the same scenario, then they had a 1 sec faster TOT than the average TOT (2.72 sec). Studies on L3 automation showed longer mean TOTs compared to L2 automation. It was also found that driving simulator fidelity did not significantly affect mean TOT. Only visual tasks had a significant effect on mean TOT. The TOT was also longer when holding a handheld device. Non-critical cases in autonomous driving were studied in [7], where visual and auditory messages alerted the driving to take control over vehicle during reading newspaper. The control transition times (CTT) reached mean value 4.4 sec and 6 sec without and with performing secondary task, respectively. There was also noted a high variance of the measured times, where a maximum CTT up to 25 sec was measured across all scenarios. Meta-analysis [8] revealed median of TOTs 2.470 (1.14-15.0) sec. The mean TOTs with respect to position of hands on the steering wheel were 2.4 sec for hands-free driving and 1.8 sec for holding the steering wheel with at least one hand during automated mode.

The difference between takeover performance in case of silent and alerted failure of autonomous system was investigated in [9, 10]. According to results [9], drivers with silent failure did not manage to keep a lane in contrast with drivers with alerted failure and had a longer TOT with generally worse lateral control quality. In alerted conditions, there was a poor longitudinal control performance due to braking the vehicle more extensively. The TOT for silent failures in autonomous driving were also studied during two types of NDRT with different difficulty [11]. The failure was alerted only by turning the steering wheel by 0.2 degrees. Up to 70 % and 30 % of participants drove out of their lane when involved in the more demanding and less demanding NDRT, respectively. Drivers took significantly longer to respond to failures that occurred on straight road segments compared to those that occurred on curved road segments and 64 % of the total number of departures were in the curved sections. By gaining experience during the driving, the reaction times were shortened gradually. When comparing different levels of autonomous systems and manual driving, it was found that drivers using active autopilot (AP) without permission to eat, drink, or use a cell phone maintained similar gaze patterns as those without AP [4]. However, non-driving tasks worsened responses to safety-critical events in L2 mode, resulting in longer reaction times compared to manual driving, with shorter glance and lane departure durations in L0 (manual) [12]. The duration of glances on the road was shown to affect takeover performance, with longer gazes off-road and hand 38

position playing a role [13]. Comparison of driver's reactions to takeover and collision in semi-autonomous and full autonomous modes was investigated in [14]. It was found that in semi-autonomous mode, the mean reaction time to starting to brake was 1.9 sec, while in full autonomous mode it took 3 sec to deactivate the autonomous system and the drivers started to brake 1 sec after deceleration of the vehicle ahead. Also, 15 sec before the event, 9 and 10 drivers out of 64 did not involve in NDRT at semi-autonomous and full autonomous mode, respectively. In semi-autonomous mode, 11 participants changed lanes, 20 only braked, and 7 participants crashed. In fully autonomous mode, 27 participants only braked, 5 of them changed lanes and no participant crashed. The use of lateral and longitudinal ADAS (L2 automation) in participants' own vehicles led to increased distracted behaviour and secondary task engagement, with drivers spending nearly 30 % of the time looking away from the road [15]. In borrowed vehicles, drivers were more engaged into secondary task during manual driving, possibly due to mistrust in the system. Using ADAS also increased both secondary task engagement and performance, reducing situation awareness and extending reaction times to critical or takeover events [3].

4.2 Takeovers on Physiological Level

The more profound way, how to inspect the driver's behavior and reactions during different scenarios with an exceed to analysis of well-being or emotions, is monitoring of driver's biological signals. Their usefulness has been extensively researched in many human-factors studies both in laboratory and real-world settings and has been significantly advanced in recent years [16, 17] with the aim to enhance driver safety, particularly in semi-autonomous driving environments. Intelligent driver monitoring systems based on physiological sensor signals can give us an information not only about crucial vital signs of the driver, but they can also provide detection of bodily states (such as drowsiness, fatigue, stress) [16, 18, 19], cognitive states (attention, perception, concentration, decision-making, problem-solving, etc.) [14, 5, 20, 2], or even emotions [21, 22]. The most commonly used physiological signals include electroencephalography (EEG) as an indicator of brain activity [23], electrocardiography (ECG) with detection of heart rate (HR) and its variability (HRV) [24], galvanic skin response (GSR) [25], pupil diameter [26], and movement of head and eyes [27]. Current technology often involves a combination of vehicle-based, behavioral, and physiological measures [18]. These multimodal features that can also integrate both subjective and objective data sources promise to enhance the accuracy and reliability of these monitoring systems, offering a holistic approach to improving driving safety [19, 28].

The takeover quality in relation to driver's physiological functions is analyzed in many studies [5, 6, 14, 26], performed generally on driving simulators, but under different conditions and scenarios. Increase in reaction time can be predicted by drowsiness and the motivational appeal of NDRTs [14]. However, the visual and mental demands of NDRTs decreased reaction time, helping drivers stay alert during partially automated driving [14]. Similarly, a negative correlation between takeover performance and cognitive load from NDRTs was found [5] with increased cognitive workload persisting even after systems were turned off [20]. Using LKS raised cognitive load and affected driving performance, with a higher standard deviation of lateral position (SDLP) and decreased time to collision (TTC) after system withdrawal [2].

It can be assumed that the mental workload (MWL), skin conductance level (SCL), and heart rate (HR) increase during the takeover periods, after which the HR drops back to a normal level quickly [6]. There is also a known increase in physiological stress markers during extreme emergency takeovers compared to moderate emergency ones through parameters like HR and pupil diameter [26]. Frontal asymmetry index (FAI) as an indicator of engagement of the drivers would slightly decrease after the takeover alerts when doing secondary tasks, the higher difficulty of which could lead to lower overall FAI during the takeover periods [6]. Similarly, the higher traffic density scenarios are associated with higher MWL, and a more difficult secondary task would lead to higher MWL and HR during the takeover activities [6]. It was found that a fake takeover alert would lead to lower overall HR, slower increase, and lower peak of SCL during the takeover period [6].

For example, EEG shows promising applications in monitoring driving scenarios associated with fatigue, dis- tracted driving, emotional changes, or MWL [23]. However, contradictory results were obtained in evaluation of EEG signals with respect to takeover quality. Classification using EEG alone showed the highest accuracy and benefits over other bio signals in [29]. Authors [27] also showed that β1, α2, β2 power together with average blink time and acceleration-y are significant for takeover quality. On the other hand, EEG-based data is not able to estimate driving performance during takeover control according to [30]. However, it is able to indicate a participant's cognitive engagement level as an indicator of distraction. During multimodal monitoring in [6], SCL and HR had slightly higher correlations with the maximum acceleration and reaction time compared to MWL, but none of them dominated the takeover readiness.

According to [31, 32], HR together with pupil diameters of drivers are valid predictors for both response time and determining the quality of takeovers in highly automated driving environments. In [33], drivers had lower HRV, narrower horizontal gaze variance, and shorter eyes-on-road time when they had a high level of cognitive load relative to a low level of cognitive load. Increased HR acceleration patterns were shown during the takeover transition stage. Heavy traffic density also resulted in increased HR acceleration patterns, inhibited blink numbers, and larger GSR phasic activation compared to light traffic density [33]. In recent years, especially cardiac activity measuring has evolved through the integration of sensor prototypes into seats, safety belts, steering wheels, or even cameras. These include mainly ECG, ballistocardiography, and seismocardiography [34, 35]. However, there are many challenges when monitoring cognitive states using in-vehicle sensors, and it is necessary to ensure valid and reliable quantification in real-world driving environments [36].

Despite the large amount of research in this area, only some studies have addressed the usability of different kinds of data processing methods based on machine learning, such as logistic regression [29], K-means [31], or XGBoost classifiers [27] with accuracy rate between

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85 % and 90 %. Deep learning was implemented by authors [37], who modelled cognitive strain in real-time scenarios using Gaussian mixture models and probabilistic neural networks when using ECG, gaze angle, and pupil diameter measurements with error rate of 10.10 %–33.03 %. Additionally, only a few studies observing stress conditions of driver based on ECG, GSR, EMG and respiration were performed under real-world driving conditions (24 – 50 minutes), such as highway, city roads, or at least the university campus [24, 25, 38]. These studies focused on using machine learning and deep learning methods for evaluation of driver stress during driving-related events or maneuvering through heavy traffic or poor conditions.

4.3 Datasets

Within the scope of Driver Behavioral Analyses, a comprehensive review of scientific literature and relevant standardization documents was conducted, focusing on driver monitoring, human–machine interaction, and takeover performance in assisted and automated driving scenarios. This review served as the foundation for defining a set of experimentally controlled yet realistic driving scenarios, designed to capture key aspects of driver behavior under varying levels of cognitive load, attention, and system intervention. Based on these findings, a structured methodology for multimodal data acquisition was established. The proposed measurement framework integrates biosignals, kinematic data, and vehicle operational signals into a synchronized data pipeline, enabling precise temporal alignment of physiological responses with driving events. Special emphasis was placed on capturing driver reaction times, particularly in safety-critical situations requiring a transition of control between the vehicle and the driver.

The experimental scenarios were designed to elicit measurable driver responses to system-initiated events, with a primary focus on the Lane Keeping Assistance System (LKAS). In this context, the dataset captures situations in which the driver is required to re-engage and correctly assume lateral control of the vehicle. The evaluation of reaction times includes both the latency of response and the quality of control takeover, providing insights into driver readiness, situational awareness, and motor response.

All collected datasets and associated materials are made available through the project's GitHub repository, ensuring transparency, reproducibility, and accessibility for further research. The repository is structured to support both high-level analysis and low-level signal processing, and includes the following data categories:

- On-board measurement platform description

  Detailed documentation of the experimental setup, including the architecture of the datalogger, connected peripheral devices, a network of 13 integrated sensors, and the supporting software framework. This section provides essential information for replicability and system understanding.

- Video recordings

  High-resolution video files capture the driver and cabin environment during experimental trials. These recordings serve as a ground truth reference for behavioral observation, event verification, and validation of sensor-based measurements.

- CAN log (UWB radar)

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Time-stamped communication data acquired from the UWB radar system via the vehicle CAN bus. These data provide information about detected micro-movements, spatial positioning, and radar-derived features relevant to in-cabin monitoring.

- Vehicle signals log

  A synchronized log of vehicle operational data, including parameters such as steering angle, vehicle speed, lateral position, and system states (e.g., LKAS activation). These signals are essential for correlating driver behavior with vehicle dynamics and system interventions.

- Bio signals log

  Physiological data acquired from the driver using multimodal sensors (e.g., ECG, EMG, respiration, EDA). These signals enable the analysis of autonomic and neuromuscular responses associated with stress, workload, and attention.

- Annotation file

  A structured set of labels describing key temporal events, such as system triggers, driver reactions, control transitions, and scenario-specific milestones. These annotations are critical for supervised analysis, machine learning applications, and precise segmentation of the dataset.

The integration of these heterogeneous data sources forms a comprehensive multimodal dataset, enabling advanced analysis of driver behavior. This includes the assessment of reaction time, control takeover performance, psychophysiological state, and interaction with driver assistance systems. The dataset is particularly suitable for the development and validation of driver monitoring systems, human-centered ADAS evaluation, and research in human factors and intelligent mobility.

Furthermore, the GitHub project is designed as a continuously evolving platform. It will be progressively extended with additional datasets covering a broader range of driving scenarios and experimental conditions. In parallel, the developed measurement platform will be made available to project partners, enabling them to acquire new datasets based on scenarios defined according to their specific research and application needs. This approach supports scalability, collaborative development, and the creation of a unified, extensible data ecosystem for driver behaviour research.

4.4 Assessment by the Ethics Committee for Biomedical Research

The activities related to Driver Behavioral Analysis are subject to assessment by the Ethics Committee for Biomedical Research at the Faculty of Electrical Engineering and Computer Science of VSB – Technical University of Ostrava (hereinafter referred to as the FEI Ethics Committee). The FEI Ethics Committee supervises compliance with ethical principles in research projects and qualification theses carried out at the Faculty of Electrical Engineering and Computer Science that involve measurements performed on human participants (research subjects).

The FEI Ethics Committee evaluates whether the dignity, freedom, health, life, safety, and privacy of all research subjects are fully respected throughout the entire course of the study.

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Particular attention is given to the adequacy of informed consent, the proportionality between the expected scientific benefits and the potential burden placed on participants, the protection of personal and biometric data, and the procedures used to anonymise and securely store collected information. These requirements are especially important in studies focused on Driver Behavioral Analysis, where physiological, behavioral, and vehicle-operation data are collected simultaneously and may be combined into complex datasets.

In order to enable the use of the developed Driver Behavioral Analysis platform and, in particular, the publication of the resulting dataset and methodology in an open-access form, the complete technical solution and data collection process will be submitted to the FEI Ethics Committee for review during April 2026. This review is necessary because the measurements are performed on human participants and include the acquisition of potentially sensitive data related to driver behaviour, reaction times, and physiological state. The ethical assessment is therefore required to ensure both the safety of participants and the protection of their rights when the research is conducted by employees and students of the faculty.

The review will also assess whether the proposed procedures comply with the relevant ethical and legal requirements for scientific research, including data minimisation, anonymisation, voluntary participation, and the possibility for participants to withdraw from the study at any time without consequences. Only data that cannot be linked back to a specific individual will be published, and all publicly released records will be processed in accordance with applicable personal data protection regulations.

The official opinion of the FEI Ethics Committee is expected to be available during April 2026. Following approval, the project repository established for this work will be made publicly available through the GitHub project repository.

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5 Conclusion

This work establishes a robust and systematically designed framework for the analysis of driver behavior in assisted and automated driving contexts. By combining an extensive review of scientific literature with relevant standardization documents, a set of experimentally controlled yet realistic driving scenarios was developed, enabling the investigation of driver responses under varying cognitive and situational conditions.

A key contribution lies in the creation of a synchronized multimodal data acquisition methodology that integrates physiological signals, vehicle dynamics, and environmental observations. This unified data pipeline allows for precise temporal alignment between driver responses and system events, providing a solid basis for analyzing reaction times, control takeover performance, and overall driver readiness in safety-critical situations. The focus on Lane Keeping Assistance System (LKAS) scenarios further ensures practical relevance, particularly in understanding driver re-engagement and lateral control transitions.

The resulting dataset represents a comprehensive resource for driver behavior research, combining biosignals, vehicle logs, radar data, video recordings, and structured annotations. Its open availability through a well-organized GitHub repository promotes transparency, reproducibility, and accessibility, supporting both fundamental research and applied development. Moreover, the dataset structure enables its use in advanced analytics, including machine learning applications and the development of driver monitoring systems.

Finally, the project is designed as a scalable and collaborative platform. With plans for continuous expansion through additional datasets and shared measurement infrastructure, it fosters cooperation among research partners and contributes to the creation of a unified ecosystem for studying human factors in intelligent mobility. Overall, this work provides a significant step toward improving the safety, reliability, and human-centered design of modern driver assistance and automated driving systems.

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