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# Toward the Definition of a Technological Set-up for Drivers' Health Status Monitoring

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**Abstract.** Driving is a high-demanding task, related to human capacity, required performance and events occurring in the external environment. In this context, the driver's health status monitoring is expected to support safety system and reduce the number of traffic accidents. Among the drivers' conditions, drowsiness and distraction are thought as crucial risk factors that may result in severe injuries. The paper defines a transdisciplinary roadmap to monitor the driver's health status and to map the perceived user experience, based on three layers: the human conditions to detect, the vital parameters to be monitored, and the adopted technologies. The paper proposes a technological set-up focusing on the driver's drowsiness detection, in the context of smart city framework and innovation 4.0. Indeed, such technologies could be embedded in the future "smart car" and communicate with external services to control the driver's performance and improve the safety inside and outside the car. A preliminary technological set-up has been realized embedded into a Maserati car.

**Keywords.** User experience, human-centred design, innovation 4.0, digital identity, human factors

## Introduction

According to the study entitled "Biometrics in the Global Automotive Industry, 2016-2025" realized by the Frost & Sullivan Intelligent Mobility team [1], by 2025 a new car in three, equal to over 34 million cars, will be equipped with biometric tools commonly used in medicine. These devices are foreseen to be able to recognize the voice, the fingerprints, to analyse the iris, to interpret the gestural commands but also to monitor the heart rhythm, to monitor the brain waves, to detect stress, to monitor tiredness, and control the blink of the eyelids, thanks to built-in technologies and cloud-based services. Thanks to such new tools and connection with wearable devices, cars will be able to carry out real check-ups of the driver first and then the passengers, reporting in real time health problems or preventing driving hazards and accidents.

Currently, a lot of research in the automotive sector is focusing on introducing new technologies for preventing accidents and providing advanced driver assistance systems. However, the state of health of a person during the driving activity is a complex concept referring to a set of physical and physiological characteristics that can include

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different aspects: the level of distraction, fatigue, attention span, and the cognitive workload. The identification of such a status is based on the complete or partial measurement of the signals that can be performed in an on-board environment. Different signals that can be collected by a driver monitoring system, from blood pressure to breath rate, from temperature to blood O2 levels [2]. Such data can be translated into information about the driver's driving style, visual attention, and behaviour, and can be combined with information on the vehicle performance as well as the environmental conditions to more fully identify the driver's status.

In this context, the present research defines a transdisciplinary roadmap to monitor the driver's health status and to map the perceived user experience for drowsiness detection. Indeed, driver fatigue is a serious problem resulting in thousands of road accidents each year, in every country. Research shows that driver fatigue may be a contributory factor in up to 20% of road accidents, and up to one quarter of fatal and serious accidents [3]. These types of crashes are about 50% more likely to result in death or serious injury, as they tend to be high-speed impacts because a driver who has fallen asleep cannot brake or swerve to avoid or reduce the impact. Indeed, drowsiness reduces the driver's reaction time, as well as vigilance, alertness and concentration. In order to prevent this issue, the National Highway Traffic Safety Administration (NHTSA) created a Drowsy Driving Research and Program Plan in 2016 developing guidelines to address both distracted and drowsy driving as well as evidence-based awareness [3], and the European New Car Assessment Programme (Euro NCAP) presented his 2025 Roadmap to introduce key protocol enhancements based on driver monitoring [4].

The research proposes also to develop a monitoring system based on three layers: the human conditions to detect, the vital parameters to be monitored, and the adopted technologies proposes to focus on the definition of an on-board system for drowsiness detection. Specifically, the research has been developed in three phases:

1. the analysis phase, based on data collection for creating and strengthening the transversal knowledge base necessary to delimit the key concepts, based on survey and exploration in the field;
2. the operational phase, which moves from the theoretical basis to the development of an non-invasive on-board system aimed at identifying the drowsiness; and
3. the demo phase, mainly focused on the development of the experimental set-up as a "demo car" equipped with biometric steering wheel, and the definition of a proper test programme to be carried out at the Modena Automotive Smart Area.

## 1. State of the art

### *1.1. Drowsiness detection on car drivers*

There are different ways to detect and measure driver drowsiness. They are normally grouped into five categories: subjective, physiological, behavioural, vehicle-based, and hybrid. Subjective tools are based on questionnaires and electro-physiological measures of sleep status. Their purpose is to provide an insight on how to more successfully predict which factors might lead to accidents and to provide means for other method groups to focus on detecting and preventing some key factors associated with driver drowsiness. The best-known subjective tests of sleepiness are: the Epworth Sleepiness Scale (ESS) [5] that quantifies the individuals' sleepiness by their tendency to fall asleep in static, no stressful situations (e.g., reading, watching television, sitting in a car at a traffic light); the Multiple Sleep Latency Test (MSLT) [6] that measures the tendency to fall asleep in a standardized sleep-promoting situation during four or five 20-min nap opportunities; the Maintenance of Wakefulness Test (MWT) [7] that monitor the user over a period of 20 minutes; the Stanford Sleepiness Scale (SSS) [8] as an instrument that contains seven statements through which people rate their current level of alertness; and the Visual Analogue Scale (VAS) [9] based on asking subjects to rate their "sleepiness" by a scale spread along a 100 mm wide line. Subjective measurement results gathered from all these tests greatly depend on the quality of the asked questions as well as proper interpretation and understanding of those questions by the subject. Due to the age and social diversity of subjects, it might not be possible to formulate a questionnaire to accommodate every potential problem. Moreover, the subjects' perspective plays a huge role on the quality of the acquired data. Lastly, it is worth stating that it is very difficult to acquire subjective drowsiness feedback from a driver in a real-world driving situation; all the measurements are usually done in a simulated environment.

Physiological methods offer an objective, precise way to measure sleepiness. They are based on the detection of physiological signals in earlier stages of drowsiness, which could allow a potential driver drowsiness detection system a little bit of extra time to alert a drowsy driver in a timely manner and thereby prevent many road accidents. The idea of being able to detect drowsiness at an early stage with very few false positives has motivated many researchers to experiment with various electro-physiological signals of the human body, such as: electrocardiogram (ECG) [10], measuring the Heart Rate Variability measure (HRV), in which the low (LF) and high (HF) frequencies of heartbeat are described; the electroencephalogram (EEG) [11], where a decrease in the power changes in the alpha frequency band and an increase in the theta frequency band indicate drowsiness; or the electro-oculogram (EOG) [12], recording the electrical potential difference between the cornea and the retina of a human eye, which can be used to monitor drivers' alertness level. The reliability and accuracy of driver drowsiness detection by using physiological signals is very high compared to other methods. However, the intrusive nature of measuring physiological signals has not allowed them, in recent years, to be installed in the real world of scenarios. Due to the technological progress in recent years, it is possible that some of the problems caused by these methods will be overcome in the future. For instance, the use of wireless devices to measure physiological signals in a less intrusive manner; or by placing electrodes on the steering wheel; or placing electrodes on the drivers seat. The obtained signals can be processed and monitored in various ways, such as using smart phone devices. Obtaining these signals in a non-intrusive way certainly contributes towards their real-world applicability.

Furthermore, the behavioural methods are based on detecting specific behavioural clues exhibited by a driver while in a drowsy state. Typical focus is on facial expressions that might express characteristics such as: rapid, constant blinking, nodding or swinging of the head, or frequent yawning. These are all tell-tale signs that a person might be sleep deprived and / or feeling drowsy. Typically, systems based on this methodology use a video camera for image acquisition and rely on a combination of computer vision and machine learning techniques to detect events of interest, measure them, and make a decision on whether the driver may be drowsy or not. For instance, when a driver is drowsy some of the muscles in the body begin to relax, leading to nodding; detecting head or eye position is a complex computer vision problem that might require stereoscopic vision or 3D vision cameras [13]. Moreover, the frequency of blinking known as PERCLOS (PERcentage of eyelid CLOSure over the pupil over time) has been devised to provide a meaningful way to correlate drowsiness with frequency of blinking [14]. Behavioural methods are considered cost effective and non-invasive, but lead to significant technical challenges. In addition to the challenges associated with the underlying computer vision, machine learning and image processing algorithms, the resulting systems are required to perform in real-time and to exhibit robustness when faced with bumpy roads, lighting changes, dirty lenses, improperly mounted cameras, and many other real-world less-than-ideal driving situations.

About vehicle-based measures for driver drowsiness detection, the Steering Wheel Movement (SWM) method [15] relies on measuring the steering wheel angle using an angle sensor mounted on the steering column, which allows for detection of even the slightest steering wheel position changes. When the driver is drowsy, the number of micro-corrections on the steering wheel is lower than the one found in normal driving conditions. Differently, the Standard Deviation of Lane Position (SDLP) [16] monitors the car's relative position within its lane with an externally mounted camera. Specialized software is used to analyse the data acquired by the camera and compute the car's position relative to the road's middle lane. Vehicle based measurements depend on specific driving conditions (such as weather, lighting, etc.) and can be used on specific roads only (with clearly marked signs and lanes). Moreover, they may lead to a large number of false positives, which would lead to a loss of confidence in the method. Behavioural measures, on the other hand, may show huge variation in the results depending on the associated lighting conditions.

It is generally believed that drowsiness is the behaviour of the central nervous system. When stress response of organs occurs during fatigue, cardiovascular nervous system will adjust accordingly. Scientific studies have established that the ECG signal, including the information of the heart rate (HR), heart rate variability (HRV) and frequency of breathe, has affinity with fatigue. HR is the number of heartbeats per unit of time, typically expressed as beats per minute (BPM); while HRV is a physiological phenomenon where the time interval between heart beats varied, which is measured by the variation in the beat-to-beat interval. Based on the results of a great number of experiments, Wilson et al. [17] concluded that HR signal is an overall indictor, which reflects the physical and mental level under different task requirement. More recently, Abe et al. [18] developed a method for predicting a drowsy driving accident based on the fact that the autonomic nervous function affects heart rate variability (HRV). However, all the researches up to date need electrode contacts on drivers' head, face, or chest. Wiring is another problem for this approach. The electrode contacts and wires will annoy the drivers, and are difficult to be implemented on vehicles. Therefore the heart rate signals are used to detect drowsiness and aims to overcome the limitation of current methods by developing non-intrusive, easily implementable and accurate heart rate sensors [19].

### *1.2. New technologies for driver's health status monitoring*

In the last decade, car drivers demonstrated a lot of interest in drivers' monitoring. Different techniques were adopted; they can be generally divided into three main categories:

1. The first category includes methods based on biomedical signals and usually; they require electrodes attached to the body, which often causes annoyance to the driver;
2. The second category includes methods based on driving behaviour; they basically evaluate variations in several signals recorded by CAN bus, which are easy to acquire;
3. The third category is based on visual assessment; computer vision can be a natural and nonintrusive technique for monitoring driver's state from face images.

Recently different systems to monitor the driver's attention and to detect drowsiness status using driving inputs cameras and sensors have been implemented. In precarious conditions, these built-in systems can alert the user and in some cases take remedial action. Attention assistance systems are slowly becoming mainstreams now with several more OEMs announcing their plans to roll out similar systems. Table 1 shows the approach adopted from the main automotive companies. It highlights that the adopted approaches hardly allow a predictive monitoring, while the Maserati approach aims at implementing special data analysis algorithms to predict risky situations.

**Table 1.** Monitoring strategies adopted by the main automotive companies

| AUTO COMPANIES | Monitoring Strategy | Alert turn off strategy/Car action | Predictive monitoring |
|---|---|---|---|
| **Audi (A8 - L3 AD)** | Eye tracking and blinking | • Seat belt tension, brake action<br>• Car stops in the current lane + eCall |  |
| **BMW** | Lane keeping monitoring | - | |
| **Jaguar/Land Rover** | Steering angle, pedals, gear lever | Press a button on the steering wheel | |
| **Mercedes** | Steering angle, pedals, gear lever | - | |
| **Tesla** | Visual monitoring | Two hands on the steering wheel | |
| **Toyota/Lexus** | Eye tracking, head motion, eyelid detection | Car deceleration | |
| **Volvo** | Face recognition, eye blinking, face and head movements | - | |
| **Volkswagen** | Steering angle, traffic signs | «Drive break»: driver pulls over and opens the door | |
| **Maserati Customer Fit** | Visual (cameras) and **tactile (steering wheel)** | Good Health Status assessment |  |

For instance, Audi FitDriver consists of a wearable device on the driver's wrist provides the data. It collects and transmits information about the most important vital signs, such as body temperature and heart rate. If Audi Fit Driver detects increased stress or fatigue, for example, the vehicle systems adapt themselves accordingly in a relaxing, a vitalizing or a protective manner. Also BMW developed a sensor system integrated into the steering wheel that can monitor the driver's state of health while driving. The device might be used recognize the heart attacks. It measures heart rate, skin conductance, and oxygen saturation sensors. Similarly, the Ford Biometric Seat Research developed a smart car with biometric sensors built into the seat, seat belt, and steering wheel they'll make sure the driver is fit to drive. The sensors monitor a driver's HR through their palms with technology like the metal pads installed on modern treadmills and stair climbers at the gym. Infrared sensors will watch for changes in a driver's temperature. Also Toyota developed a sensor system integrated in the steering wheel that is capable to monitor the driver's health conditions including inception of heart attacks and fainting spells. During driving, the steering monitors various factors of human health including heat rate, oxygen saturation and electric conductance of the skin using two sensors integrated into the steering. The sensors use infrared light to the fingers to measure these aspects, so the fingers should be in contact with the sensors always. The collected data is then transferred to a micro-controller that transforms the electric signal to show on the information system display of the vehicle.

However, all this systems are mainly prototypes and they are still far from a real introduction in cars and an effective diffusion. The main problems relate to system reliability, data interpretation, and lack in integration into a V2X framework. This research aims at defining a testing set-up to be mounted on a real car, for an effective application.

## 2. The research approach

The research approach is based on the relationship between arousal level and performance; indeed, it has been largely demonstrated that the quality of the driver's performance is significantly impacted by the level of arousal and the ability to appropriately attend to relevant events [20]. Underlying this principle of behaviour is the observation that both fatigue (under arousal) and stress (over arousal) are associated with decreasing performance. Optimal performance occurs in a range between these extremes where the level of arousal and attention is appropriately balanced for the demands of the task. From this perspective, the ability to sense and, as needed, encourage and support the driver in moving to a more optimal state of arousal is one of the next frontiers in automotive safety. In this context, monitoring the psychophysiological status of the driver plays a fundamental role for introducing on proper human monitoring system able to continuously monitor the driver's conditions. ON this basis, a roadmap to study the driver's user experience (UX) has been defined, as shown in Figure 1. Three layers are considered: the psychophysiological processes, the vital parameters to be monitored, and the associated detection technologies. In particular, the research has been organized into 3 phases:

1. Analysis of driver's drowsiness and distraction;
2. Analysis of the level of driver's physical stress;
3. Analysis of the level of psychophysical stress and emotions.

The present study focuses on phase 1, with particular attention to the monitoring of driver's drowsiness. The following phases will be implemented later on. Scientific research has found that the variations in the Heart Rate Variability (HRV) can detect different physical conditions, among which drowsiness. Throughout a normal sinus rhythm, the heart rate (HR) changes over time of the period between successive heartbeats. Heart rate variability (HRV) is derived from the dynamic interplay from the various physiologic mechanisms which control the instantaneous HR. HRV is assumed to reflect the heart's capability to adapt to changing circumstances by detecting and rapidly responding to unpredictable stimuli. From drowsiness detection, this study considers that at the beginning of sleep, low frequency to high frequency ratio in HRV signals decreases; also sudden decrease in HR occurs. Figure 2 presents the adopted approach for the drivers' drowsiness detection. It underlines the importance of detecting HRV through an ECG sensor and monitoring of various parameters through several technologies in order to identify drowsiness status.

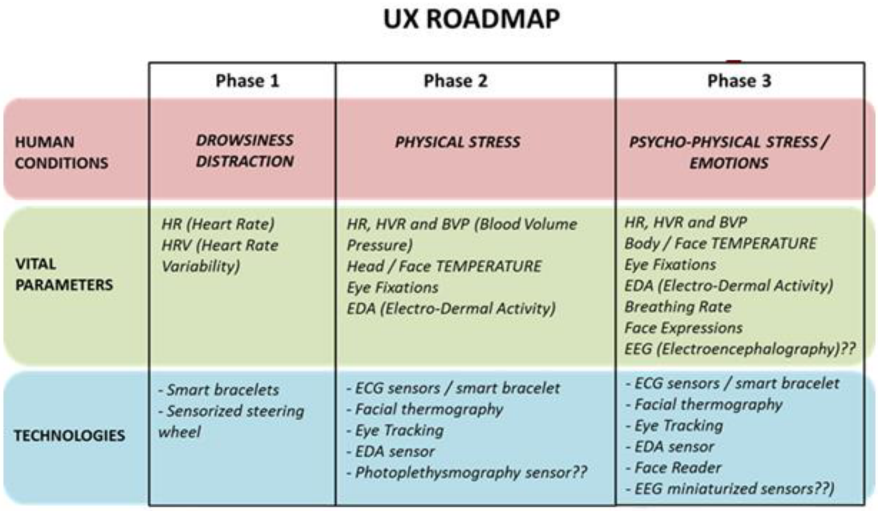


**Figure 1.** Roadmap for the driver's User eXperience monitoring.

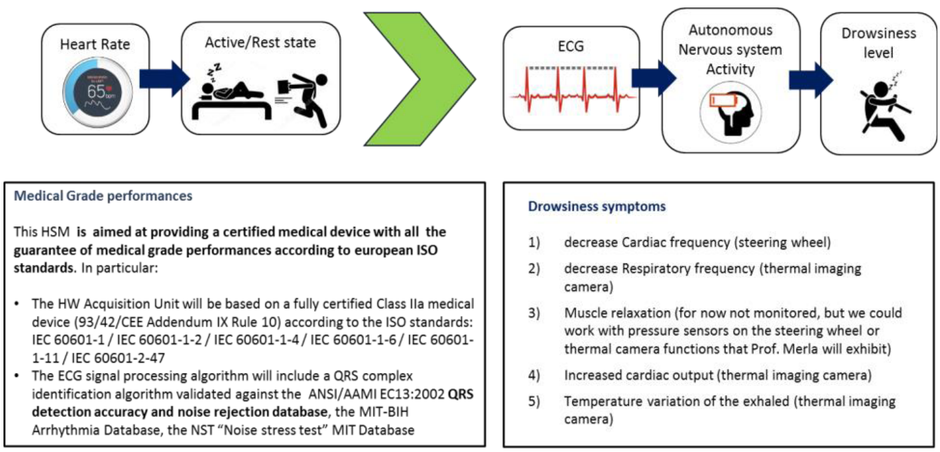


**Figure 2.** Driver's drowsiness detection approach.

## 3. The technological set-up

The proposed set-up is based on a non-invasive electrocardiogram (ECG) system for HR and HRV measurement, and an algorithm to properly process the obtained data. Such a system acquires the heart signals from a set of proper sensors embedded into the steering wheel and measured by the contact with the user's hands. Two conductive surfaces have been embedded in the steering wheel, using an existing Maserati Wood Styling Ring and modify to include metal sensors (Figure 3). Each sensor has been coupled with a wire terminating in a snap button connector. The HW Acquisition Unit (supplied by Vacust) is powered by a lithium battery, which is activated with two hands on the steering wheel after 1 second. Battery recharging takes place by temporarily removing the device from the SW when needed. Finally, the system is able to transmit the collected data via Bluetooth smart and Ant + (Android and iOS compliant) to any Health & Fitness Apps.

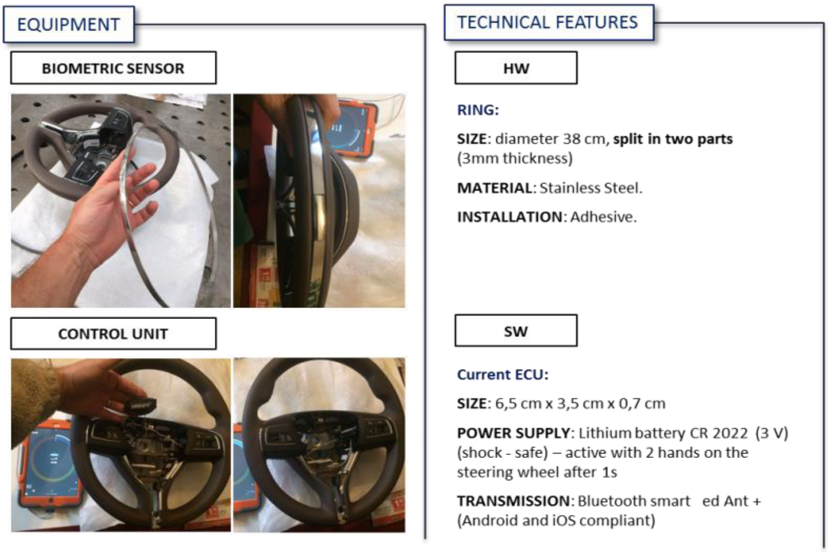


**Figure 3.** The experimental set-up.

The proposed set-up has been arranged into a real car and used for preliminary tests with users. The sensorized steering wheel has been also combined with a thermal camera and a depth camera for face recognition and analysis of physical behaviours. Data collected from the sensorized steering wheel allowed collecting HR and HRV signal in real time during driving activity with a good confidence (Figure 4).

**Figure 4.** Example of experimental test on a real vehicle.

Experimental results proved that the system is suitable for a further development toward the real implementation into an effective car environment. On the contrary, experimental data highlighted that users have to position both hands on the steering wheel in order to collect a proper data signal, which represents a limitation for its applicability. Further works will be oriented to developing a more robust HR and HVR recording and to interpreting the recorded signals by a more structured test phase. The research is also a step the integration of driver's human monitoring technologies with the so-called "V2X" framework, where Vehicle-to-Vehicle and Vehicle-to-Infrastructure communication systems are able to interact with a set of services to support the driver and to achieve higher degree of safety and prevention (Figure 5).

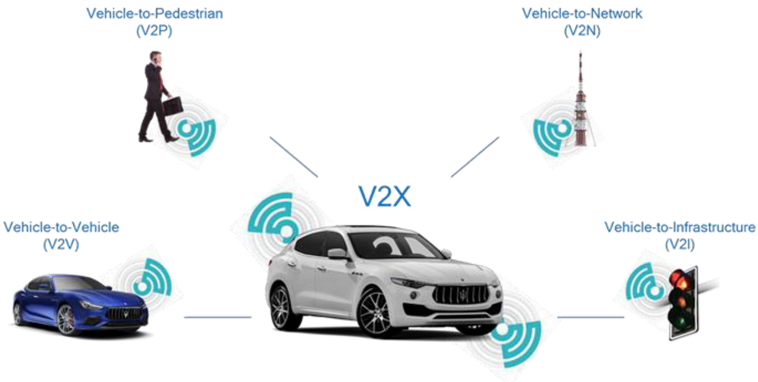


**Figure 5.** V2X framework for the future cars.

## 4. Conclusions

The research defined a transdisciplinary roadmap to monitor the driver's health status and to map the perceived user experience, based on three layers: the human conditions to detect, the vital parameters to be monitored, and the adopted technologies. Furthermore, it presented a preliminary technological set-up focusing on the driver's drowsiness detection, to be embedded in the future "smart car". Next steps will be focused on the integration of next generation devices, able to record an electrocardiogram (ECG) with a dedicated control unit, into the steering wheel, by using conductive plastics instead of steel, and in the definition of a set of robust algorithm validation tests. Furthermore, also the user interface has to be developed to provide feedback on ADAS (Advanced driver assistance systems): from providing text / graphic message, to audio alert, vibrations in the driver's seat, rest area suggestion on navigator, etc. Obviously, the roadmap suggests also to extend the monitoring to other parameters (phase 2 and 3 of the UX roadmap), until data transmission to medical centres (Figure 6).

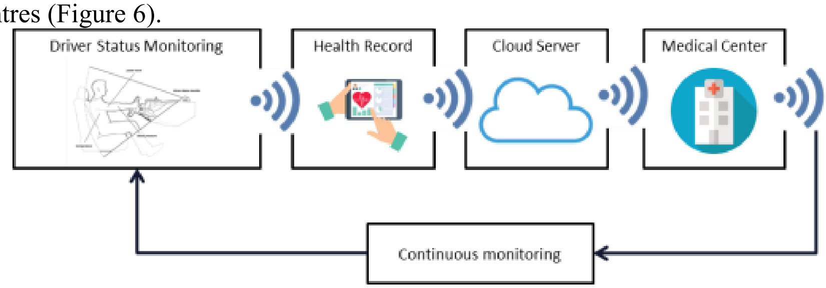


**Figure 6.** Future scenario for driver status monitoring set-up.

## References


[1] Frost and Sullivan, 2016, *Biometrics in the Global Automotive Industry*, 2016-2025, Accessed: Feb, 2 2018, https://store.frost.com/biometrics-in-the-global-automotive-industry-2016-2025.html

[2] J.F. Coughlin, B. Reimer and B. Mehler, *Driver Wellness, Safety & the Development of an AwareCar*, Massachusetts Institute of Technology Center for Transportation & Logistics AgeLab, 2009, Accessed: Jan, 30 2018, http://web.mit.edu/reimer/www/pdfs/coughlin_wellness_2009.pdf.

[3] NHTSA, 2016, *NHTSA Drowsy Driving Research and Program Plan*. Accessed: Jan, 03 2018, https://www.nhtsa.gov/

[4] EuroNCAP (2017). *Euro NCAP 2025 Roadmap in pursuit Vision Zero*. Accessed: Jan, 03 2018, https://www.euroncap.com/en/for-engineers/technical-papers/

[5] M. Johns, A new method for measuring daytime sleepiness: the Epworth sleepiness scale, *Sleep*, Vol. 14 (6), 1991, pp. 540–545.

[6] M.A. Carskadon, W.C. Dement, M.M. Mitler, T. Roth, P.R. Westbrook, S. Keenan, Guidelines for the multiple sleep latency test (MSLT): a standard measure of sleepiness, *Sleep*, Vol. 9, 1989, pp. 519–524.

[7] W. Liu, Y. Wang and L. Jia, An effective eye states detection method based on projection. In S*ignal Processing (ICSP), 2010 IEEE 10th International Conference on*, 2010, pp. 829–831.

[8] E. Hoddes, V. Zarcone, H. Smythe, R. Phillips and W.C. Dement, Quantification of sleepiness: a new approach. *Psychophysiology*, Vol. 10 (4), 1973, pp. 431–436.

[9] M.E. Wewers and N.K. Lowe, A critical review of visual analogue scales in the measurement of clinical phenomena, *Res Nurs Health*, Vol. 13 (4), 1990, pp. 227–236.

[10] R. Khushaba, S. Kodagoda, S. Lal and G. Dissanayake, Driver drowsiness classification using fuzzy wavelet-packet-based feature-extraction algorithm, *Biomedical Engineering, IEEE Transactions on*, Vol. 58 (1), 1990, pp. 121–131.

[11] M. Akin, M.B. Kurt, N. Sezgin and M. Bayram, Estimating vigilance level by using EEG and EMG signals, *Neural Comput. Appl*., Vol. 17 (3) , 2008, pp: 227–236.

[12] S. Hu and G. Zheng. Driver drowsiness detection with eyelid related parameters by Support Vector Machine, *Expert Syst. Appl.*, Vol. 36 (4), 2009, pp: 7651–7658.

[13] E.M. Chutorian and M. Trivedi. Head pose estimation and augmented reality tracking: An integrated system and evaluation for monitoring driver awareness, *Intelligent Transportation Systems, IEEE Transactions on*, Vol. 11 (2), 2010, pp. 300–311.

[14] A. Lenskiy and J.S. Lee. Driver's eye blinking detection using novel color and texture segmentation algorithms. *International Journal of Control, Automation and Systems*, Vol. 10 (2), 2012, pp. 317–327.

[15] R. Feng, G. Zhang and B. Cheng, An on-board system for detecting driver drowsiness based on multi-sensor data fusion using Dempster-Shafer theory, *In Networking, Sensing and Control*, ICNSC, 2009, DOI: 10.1109/ICNSC.2009.4919399.

[16] M. Ingre, T. Akerstedt, B. Peters, A. Anund and G. Kecklund, Subjective sleepiness, simulated driving performance and blink duration: examining individual differences, *Journal of Sleep Research*, Vol. 15 (1), 2006, pp. 47–53.

[17] G.F. Wilson and R.D. Donnel, Measurement of operator workload with the neuropsychological workload test battery, *Advances in Psychology*, Vol. 52, 1988, pp. 63-100.

[18] E. Abe, K. Fujiwara, T. Hiraoka, T. Yamakawa and M. Kano, Development of Drowsy Driving Accident Prediction by Heart Rate Variability Analysis, *In Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific*, Cambodia, 2014, DOI: 10.1109/APSIPA.2014.7041787.

[19] A. Bonjyotsna and S. Roy, Correlation of drowsiness with electrocardiogram: a review, *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, Vol. 3 (5), 2014, pp. 9538-9544.

[20] R.M. Yerkes and J.D. Dodson, The relation of strength of stimulus to rapidity of habit formation, *Journal of Comparative Neurology & Psychology*, Vol. 18, 1908, pp. 459-482.