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CICLO XXXVII

INSIGHTS INTO THE PSYCHOPHYSIOLOGICAL STATE OF CAR DRIVERS

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To my family and loved ones,
who have always believed in me

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ABSTRACT

Driving a vehicle is a complex and dynamic activity performed daily by millions of individuals, requiring an optimal psychophysiological state to ensure safe operation. Due to the high number of traffic accidents, road safety has become an international concern and an investigation into the factors that influence driving behaviour may facilitate the development of technologies designed to monitor drivers and enhance human well-being. Peripheral and non-invasive physiological measures can reveal affective and cognitive states and could provide insights into a driver's mental state and workload while driving. The main goal of this thesis was to explore and monitor the driver's physiological state in both real and simulated driving contexts and to examine the effects of various factors, both environmental and human, that can potentially cause changes in driving behaviour and alter the driver's psychophysiological state. This work includes three studies, each of which sought to contribute to the existing body of knowledge on the extent to which and the manner in which these factors can influence the driver's psycho-physiological state. In the first study, we aimed to monitor the driver's cardiac autonomic activity during real road driving, assuming psychophysiological variations based on driving context and psychosocial stress induced in urban environments. We considered psychological factors, sex and driving experience as potential modulatory components for cardiac autonomic responses during driving. Heart rate (HR) and heart rate variability (HRV) were measured during actual driving tasks in a sample of male and female drivers, with psychometric characteristics collected using questionnaires. HRV analysis revealed a significant overall autonomic activation while driving, independent from the exposure to external stressors. Neither sex nor driving experience seemed to affect cardiac autonomic response to driving. A significant positive correlation emerged between anxiety/stress symptoms and aberrant driving behaviour. The second study explored the effects of mental workload due to distracted

driving on the driver's physiological state. The goal was pursued by monitoring cardiac autonomic activity during a simulated low-traffic highway scenario, in which the participant was subjected to various distraction tasks. We expected variations according to the amount of mental workload derived from distractive stimuli during the primary driving task and we considered sex as potential explanatory factor for psychophysiological modulation during driving. HRV analysis revealed significant overall autonomic activation during driving, independent of exposure to additional secondary distractive tasks and sex. In summary, the results of both studies suggest that driving has a significant impact on cardiac autonomic neural modulation, also demonstrating that peripheral biomarkers such as HRV are useful for providing information on ecological and everyday situations such as driving activity. The third and final study in this thesis investigated a mental and physical risk condition during driving, typically characterised by low physiological activation: fatigue. We sought to assess validity of physiological indices, such as nasal skin temperature and heart rate, in detecting changes in arousal levels during 3-h monotonous driving, a common scenario for inducing fatigue while driving. Driving mode conditions (autonomous and manual driving) were included in the experimental protocol as a possible modulation factor of the driver's physiological response to fatigue due to prolonged driving. Our results showed no evidence of physiological deactivation due to fatigue from driving time. The use of autonomous driving or changing driving mode mid-activity may have contributed to mitigating the effects of fatigue on physiological parameters classically observed in paradigms with prolonged monotonous driving. In conclusion, this thesis adds to the current literature by examining psychophysiological activity while driving in both real and simulated driving environments. It emphasises the importance of considering the psychophysiological approach as a valid method in the field of driving safety, with the potential to add useful knowledge for the development of biometric sensors that can be applied to monitor the driver's state and,

through artificial intelligence, manage risk situations related to distraction, fatigue or emotional states while driving.

CHAPTER 1. – General Introduction

1.1 Risks behind the wheel: Environmental and Human factors in driving behaviour

Driving is one of the major experiences linking together people and this activity involves both physical and psychological domains. Perception, attention, learning, memory, decision-making and action control are essential to perform the task correctly (Groeger, J. A ,2013). Recently, there has been a growing focus on understanding tasks that drivers perform every day while driving. In one model, driving tasks were classified into three categories of skill and control, from the lowest to the highest level of involvement of cognitive resources (Michon, 1985, 1979). The general plans and re-planning of the driving itinerary based on various factors (i.e., unexpected closed road) are managed at *Strategical level,* which is the highest level of cognitive activity but with a little time constraints. At the middle, the *Tactical level*, drivers control pre-planned actions and adapt their behaviour according to the dynamic driving environment and their intentions, such as adjusting the vehicle speed before turning, deciding to stop at a pedestrian crossing, or avoiding an obstacle. This category task requires average levels of both cognitive resources and time constraints. Lastly, *Operational level* is the bottom task which does not require cognitive effort but must be carried out under very tight time restrictions. Here implicit driving abilities are dedicated to the physical control of the vehicle by handling the steering wheel, the brake and accelerator pedals and manage gear changes with manual gearboxes (Navarro et al., 2018). Therefore, driving is a complex behaviour which requires an optimum psychophysiological state to conduct the vehicle safely. Loss of any of these functions or altered psychophysiological state can increase the risk of making driving mistakes, resulting in an increased risk of traffic accidents. According to the World Health Organisation report, 1.19 million people around the world lose their lives each year in road accidents, which are the leading cause of death for children and young adults between the ages of 5 and 29 (WHO, Road traffic injuries, Apr. 2024). The Italian National Institute of Statistics (ISTAT) published a report on

the Italian road safety situation in 2022, and it was estimated that the highest mortality rate in road accidents occurs in the 85-89 years and 20-24 years groups (Istat, 2022). Furthermore, it was found that the riskiest type of road for accidents was urban (figure 1, 2). Road safety has become an international concern and is central to the European Union's recent mobility policy initiatives, which aim to halve road accidents and serious injuries by 2030 and approach zero by 2050 (EU Road Safety Policy Framework 2021-2030).

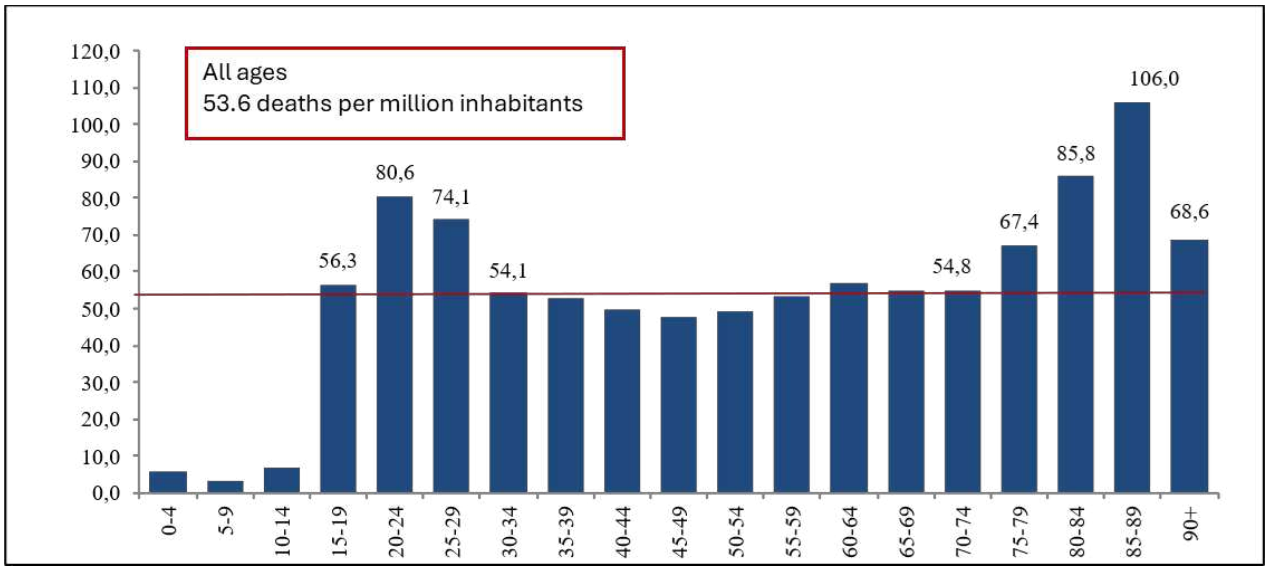

Figure 1. *Road Mortality rate by class of age in Italy. Year 2022, per million inhabitants. Data are from ISTAT REPORT 2022. The original language was modified for this work.*

2022

Categories of road type	Road accidents	Road traffic death	Road traffic injuries	Mortality rate	Var.% Accidents 2022/2021	Var.% Death 2022/2021	Var.% Injuries 2022/2021
Urban road	121.818	1.333	155.934	1,1	9,8	5,5	9,3
Highway	8.375	295	13.579	3,5	9,7	19,9	12,9
Other road type	35.696	1.531	53.962	4,3	7,2	12,2	8,0
Tot.	165.889	3.159	223.475	1,9	9,2	9,9	9,2

Figure 2.*Road traffic accidents with personal injuries by road category in Italy. Years 2022, 2021 and 2019, absolute values and percentage changes 2022/2021 and 2022/2019. Data are from ISTAT REPORT 2022. The original language was modified for this work.*

For these reasons, understanding and identifying the factors that influence road accident risk is of considerable importance in improving road safety and human well-being. Several studies have shown that internal factors (i.e., emotions, mental workload, sleep quality) and external factors (i.e., road conditions) can interfere with safe driving. Moreover, socio-demographic characteristics could explain heterogeneity outcomes in driving behaviour (i.e., sex, driving experience). Environmental settings such as road design (motorways vs urban roads), traffic flow (high vs low) as well as weather can influence and increase driving-related stress (Dwight and David, 1997; Hill and Boyle 2007, Healey and Picard, 2005; Westerink et al., 2008). By interviewing, Dwight and David found that perceived driving stress and aggressive driving behaviours were greater in high traffic jam areas than in low congestion areas. Hill and Boyle assessed drivers' stress under various external conditions (roads, traffic flow, and weather). They have shown that driving stress was influenced by environmental types and driving distances. Additionally, Healey and Picard (2005) and Westerink et al. (2008) have reported that city driving was more stressful than motorways. In addition to external factors, the driver's mental and emotional state is a crucial element in understanding driving behaviour and the associated risks. Many studies have examined the human factors associated with driving safety and have found that an altered emotional and mental state impairs effectiveness behind the wheel. Welch and colleagues have reviewed affective states related to driving behaviour and have identified which emotional conditions can result in safety and unsafety behaviour (Welch et al., 2019). Taking the Russel model into account (Russel,1980), affective states can be distinguished by the combination of two dimensions, the valence (pleasant vs. unpleasant) and level of arousal state (activation vs. deactivation). In the Welch review, Russel's model was adapted to describe the relationship between the emotional state and driving outcomes (figure 3). It has been observed that the unpleasant emotional dimension combined with the altered state of arousal, both high and low, are risk factors for driving. For instance, high-arousal states, such as anger or stress,

lead to a higher risk of dangerous behaviour, such as driving faster, committing more traffic violations and underestimating risk situations (Cunningham et al., 2016; Zhang e al., 2016; Precht et al., 2017; Li et al., 2019). In addition, stress can be the result of the driver's perceived level of cognitive workload. In other words, cognitive workload is associated with the amount of “mental capacity” employed by humans to perform a task. When demands exceed capacity, a negative condition, known as distress, occurs. The resulting distress is associated with road accidents (Brookhuis and De Waard, 2010). To study the effects of negative emotion or stress on driving, several methods have been applied to manipulate general emotion and traffic-related emotions (Gilet, 2008; Fairclough and Spiridon, 2012; Stephens and Groeger, 2014). By inducing negative emotions through listening to personal experiences or manipulating the characteristics of the driving scenario, a change in driving behaviour was observed. Drivers were more inclined to commit traffic safety violations and experienced greater emotion of anger. In addition, many studies have used the dual-task induction technique to manipulate driver workload (Hidalgo-Muñoz et al., 2019; Lanatà et al., 2014). For instance, the participant carries out the driving task and simultaneously performs a cognitive task involving working memory. The secondary cognitive task most commonly used in driving studies as a cognitive load manipulation is the N-back task. It consists of a sequence of stimuli and requires the participant to indicate when the current stimulus matches that of n previous steps in the sequence.

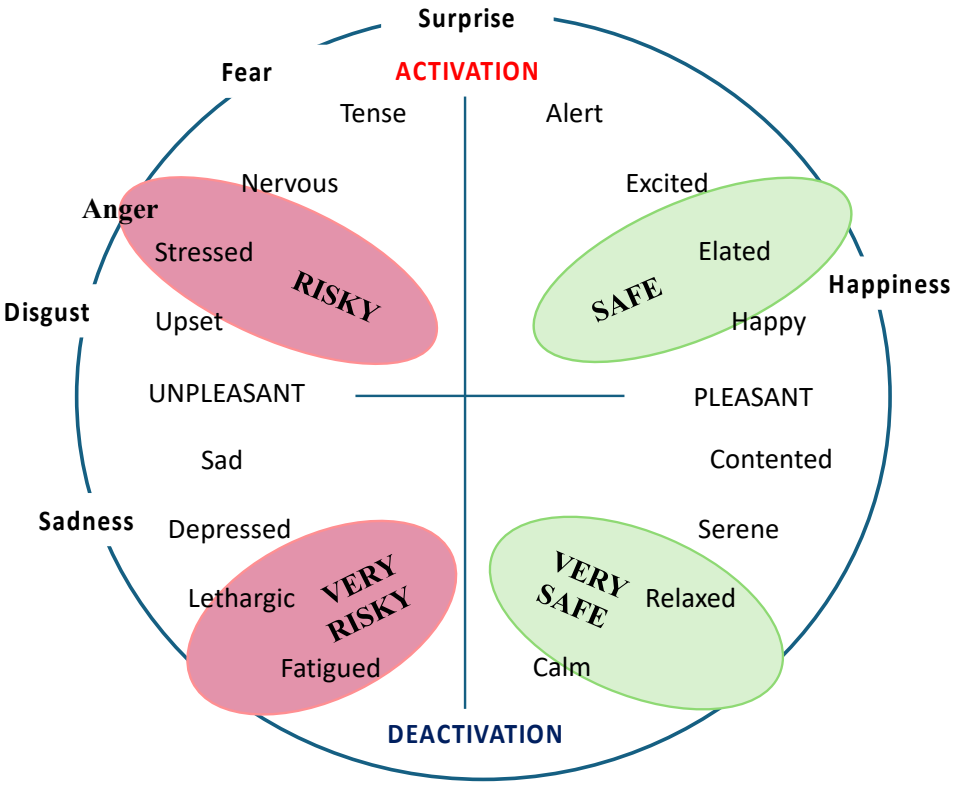

Figure 3. *The Russel's affective circle adjusted for driving risk factors. The four coloured ovals represent which mental and emotional states are likely to be related to safer (green ovals) or riskier (red ovals) driving behaviours. This figure is taken from the review by Welch and colleagues (2019).*

Focusing on the low-arousal states, fatigue and poor-quality sleep are considered to be the main causes in road traffic accidents. Fatigue is a multidimensional concept that involves physical and mental fatigue, and can result from a variety of causes, such as an overload of an individual's cognitive resources, or occur as a result of sleep deficiency (May and Baldwin 2009). It includes symptoms as difficulty in maintaining attention, concentration, focus, vigilance and staying awake (Soares et al., 2019). In driving context, driver fatigue leads to impaired reaction times, reduced vigilance, information processing deficits, and lapsed attention, which are all extremely dangerous while operating a vehicle (Zeng et al., 2024). Furthermore, it has been observed that driving time could be an explanatory factor for driver fatigue (Di Stasi et al., 2015). In fact, monotonous and simultaneously prolonged driving can impair alertness required for safe driving (Aidman et al.,

2015). Moreover, time of the day is considered an important risk factor in road accidents. Fatigue-related accidents are most frequently observed between 2 a.m. and 6 a.m. and again between 2 p.m. and 4 p.m (Williamson &Friswell, 2011). In driving research, fatigue is investigated by manipulating driving time and driving scenario. The most common technique for inducing driver fatigue is exposure to a monotonous driving scenario and driving for more than three hours (Li et al., 2009; Kee et al., 2010; Fu et al., 2016). Therefore, human characteristics can explain the risks behind the wheel and it is important to take them into account when studying drivers. Being in an altered mental and emotional state can lead to serious risks not only for oneself but for other road users. In addition, driver's demographical characteristics (such as sex, age and accident history) have been studied in relation to driving behaviour. Sex and age differences were observed in risky driving behaviour. Most studies suggest that male drivers drive more aggressively than female drivers, increasing the risk of crashing (Rhodes and Pivik, 2011). Moreover, various studies have shown that sex and age are demographic factors correlated with Driving Behaviour Questionnaire (DBQ). The DBQ is a widely used measure of aberrant driving behaviour (Reason et al., 1990). The questionnaire measures aberrant driving behaviours, which are divided into errors and violations. Errors depend on a failure in the cognitive process of action planning, whereas violations are caused by deliberate and intentional actions against the traffic road rules (Lucidi et al., 2010). Male exhibit more violations and lapses than women drivers (Rezapur-Shahkolai et al., 2020; Cordellieri et al., 2016). However, female drivers make more errors than male drivers (De Winter and Dodou, 2010). In addition, young drivers are more likely to experience accidents than older drivers. This may be due to the fact that young drivers tend to overestimate their driving ability (Singh and Kathuria,2021). It has been observed that young drivers (19–25 years) exhibited more aberrant driving behaviours compared with middle-aged drivers (26–59 years) (Arafa et al., 2020). Apart from sex and age, driving experience has been identified as a risk factor for traffic accidents. Indeed, aberrant driving

behaviours and traffic violations are higher within the first three years after licensure (Roman et al., 2015).

1.2 Physiological measures to estimate driver's arousal state

It is well known that affective state and the level of mental workload influence the physiological state of the subject. Under conditions of stress, increased workload or fatigue, a series of neurovegetative responses, mediated by the autonomic nervous system (ANS), are elicited. The role of the ANS in emotion has been demonstrated in numerous studies assessing various aspects of the ANS-emotional relationship (for a review, see Kreibig, 2010). ANS is generally conceived to have two major branches: the sympathetic system (SNP), associated with energy mobilization and the parasympathetic (PNS) associated with vegetative and restorative functions. Like many organs in the body, the heart is dually innervated by the SNS and PNS, specifically at the sinoatrial (SA) node (Figure 4). In a healthy heart, Heart Rate (HR) is influenced by the balance between the neural activity of the parasympathetic (vagus) nerves, which slow the heart rate, and the sympathetic nerves, which speed it up. At rest, both sympathetic and parasympathetic nerves are tonically active and vagal effects are dominant. Therefore, HR reflects the relative activity of the sympathetic and parasympathetic systems (Shaffer et al., 2014). Moreover, the ANS controls cutaneous blood perfusion, in particular SNS is responsible for vasoconstriction, whereas the effect of PNS activation is vasodilatation, which results in modifications of body human temperature (Ioannou et al., 2014). Therefore, in the light of this dynamism between the central nervous system (SNC) and the autonomic nervous system in response to emotional and cognitive stimuli, it is possible to derive information on the psycho-physiological state through a series of peripheral and non-invasive measures: Heart rate variability and Thermal infrared imaging. Both physiological measures can reveal the subject's affective and cognitive state, and monitoring peripheral physiological activities can provide insight into the driver's mental state and workload.

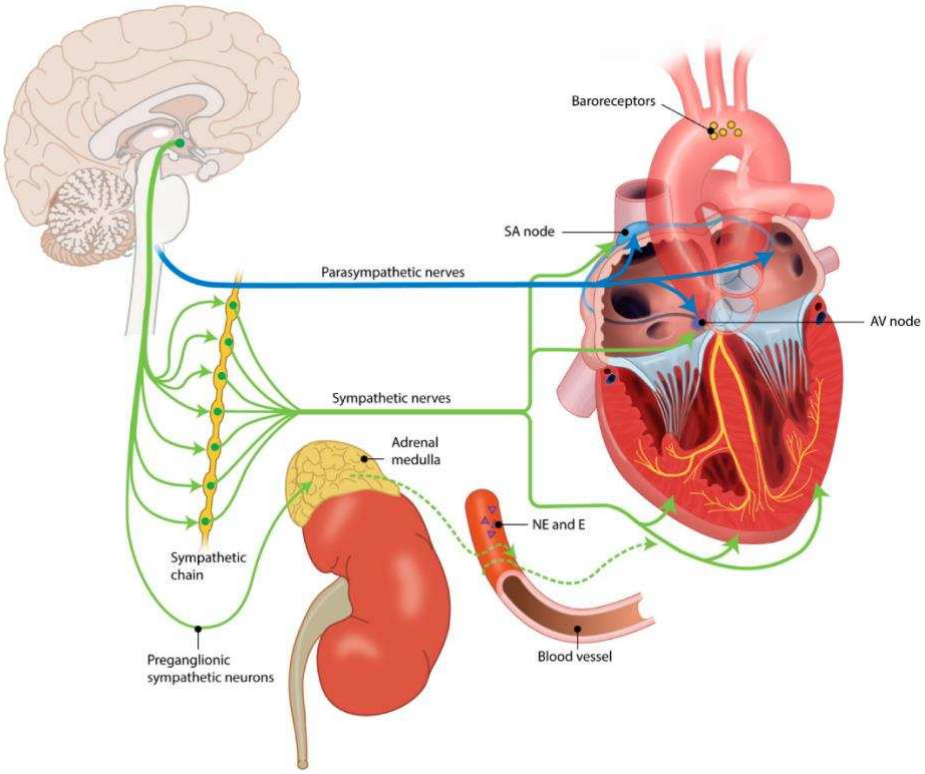

Figure 4. *Autonomic cardiovascular control.*

1.2.1 The applicability of Heart Rate Variability analysis in the driving context

Heart rate variability (HRV) is an indirect, non-invasive measurement of beat-to-beat temporal changes in heart rate, which reflect the dynamic changes of cardiac autonomic modulation at the sinoatrial node of the heart, but more specifically is able to index cardiac vagal tone. The electrical activity of the heart can be obtained by means of electrocardiography (ECG). HRV analysis has been applied in various research fields including psychophysiology, cardiology and psychiatry, and has been increasingly recognized as a biomarker of health and stress. A healthy subject is characterized by higher levels of resting HRV, which are associated with better flexibility and adaptability to environmental challenges. Moreover, HRV analysis is able to index psychophysiological states during stressful conditions or mental efforts (Thayer et al., 2009). HRV is quantified by analysing the variations of the time intervals between consecutive normal heart beats and is traditionally

performed by applying time-domain and frequency-domain methods. The time domain parameters are calculated with mathematical approaches to measure the amount of variability present in a specific time period in a continuous ECG signal. The most frequently used time domain indexes of HRV are the SDNN, RMSSD and pNN50. The SDNN is the standard deviation of the average R-R interval, and it estimates overall HRV and therefore includes the contribution of both branches of the ANS to HR variations. The RMSSD is the root mean square of successive differences between adjacent R-R intervals, and it estimates vagally mediated changes in HR. The pNN50 quantifies the percentage of successive R-R interval differences that are larger than 50 ms and reflects vagal tone (Laborde, Mosley, & Thayer, 2017). Analysis in the frequency-domain requires filtering the signal into different bands. In fact, power spectral analysis decomposes a time-dependent fluctuating signal into its sinusoidal components and allows to detect and quantify the amount of cyclical variation present at different frequencies (Malliani et al., 1991). It provides information of how power is distributed as a function of frequency and in a typical power spectral density curve three main frequency bands can be identified: the very low frequency (VLF), low frequency (LF) and high frequency (HF) bands. The VLF component (<0.04 Hz) reflects R-R interval variations that are due to long-term regulation mechanisms (i.e. thermoregulation and hormonal mechanisms). The LF band (0.04-0.15 Hz) reflects a mix between sympathetic and vagal influences. Lastly, the HF band (0.15-0.4 Hz) reflects vagal tone and is linked to respiratory-related changes in cardiac autonomic modulation (Shaffer et al., 2014).

In driving research field, several studies have demonstrated the effectiveness of HRV measures in in real and simulated driving scenarios, under stress and fatigue conditions. In other words, it has been investigated how driver psychophysiologically responds in over and under - arousal conditions. As illustrated, environmental and human factors (e.g., level of perceived workload, experienced emotional status, sleep quality) can decrease the effectiveness of being behind the wheel and may

provoke physiological changes while driving. Focusing on environmental settings, an increase in cardiac autonomic activation was observed while driving in an urban context compared to driving on highways (Tavakoli et al., 2020; Riener et al., 2009). The cognitive demands in the urban context are greater than in the highway context, the driver must pay attention to changing traffic lights, crosswalks, and everything is more unpredictable. Indeed, challenging or unexpected traffic situations, which can result in frustration and anger, have been shown to be associated with unsafe, risky and aggressive driving behaviours (Lee and Winston, 2016). In addition, situations of unpredictability and uncontrollability can generate the conditions in which environmental demands exceed an organism's natural regulatory capacity (Koolhaas et al., 2011). Furthermore, many studies have used the dual-task induction technique to manipulate the amount of workload (Hidalgo-Muñoz et al., 2019; Lanatà et al., 2014). Heine et al. (2017) measured autonomic activity during a simulated driving task at the same time as performing a secondary cognitive task. They applied the *n-back task*, also known as the digital recall task (Mehler et al., 2011). Increased heart rate and decreased heart rate variability were observed with high cognitive workload. These findings were also observed in an on real road study (Mehler et al., 2012). The participants performed the n-back task while driving following the directions of the experimenter. They detected an increase in heart rate and skin conductance level with each incremental increase in cognitive demand.

In addition, some studies have applied HRV analysis to detect the driver's psychophysiological state under conditions of low arousal, such as fatigue and reduced sleep quality. As already mentioned, fatigue and condition of sleep deprivation can impair the attentional resources required to perform the driving task, resulting in an increased risk of road accidents. Driver fatigue can be caused by prolonged or monotonous driving situations. Indeed, a simulated driving study monitored physiological parameters after 2-hours driving. Compared to the beginning of the driving task, heart rate and LF/HF decreased, as well increased fatigue symptoms after driving (Liang et al., 2009).

Schmidt and colleagues (2009) studied the effects of monotonous daytime driving on vigilance state in a real-world driving context. The participants performed a driving task of approximately four hours on a low-traffic motorway outside rush hour. The authors observed a continuous reduction in vigilance indicated by all performance and physiological measures. In particular, the results showed a linear decrease in heart rate until the end of the task. Another study assessed mental fatigue in a sample of professional bus drivers through HRV indices. Compared to the start of the task, a decrease in HR was observed after 3 hours of driving and this effect was maintained until the end of the experiment, after 6 hours total driving time (Lecca et al., 2022). Therefore, the use of physiological signals such as HRV can be useful in revealing the driver's physiological state, both under fatigue and drowsiness, and under stressful conditions while driving.

1.2.2 The applicability of Thermal Infrared Imaging in the driving context

In the last years, a new way of tracking cognitive states has been opened up by the ability to use thermographic cameras to measure skin temperature. Thermal infrared imaging (TII) is a non-invasive instrument for assessing body temperature, monitoring human arousal and estimating breathing rate. The TII records the body's naturally emitted thermal irradiation and detects variations of the cutaneous surface. The latter depends on the blood perfusion controlled by the autonomic nervous system, which controls the vessels that irrigate the skin and change with emotional states (Ioannou et al., 2014, Hassoumi et al., 2022) (Figure 5). It is useful for detecting drowsiness, stress and other emotional states and it has been applied in various research fields including medicine, cognitive psychology and the safety. Over the years, several regions of interest (ROIs) have been considered to study thermal changes due to different emotional and mental tasks. For instance, emotional arousal, mental stress, and mental workload were investigated through the temperature of the nose tip (Cho et al., 2019), forehead (Hassoumi et al., 2022), upper lips, cheekbones, the surrounding area of the eyes, and corrugator muscles of the face (Aristizabal-Tique

et al., 2023).

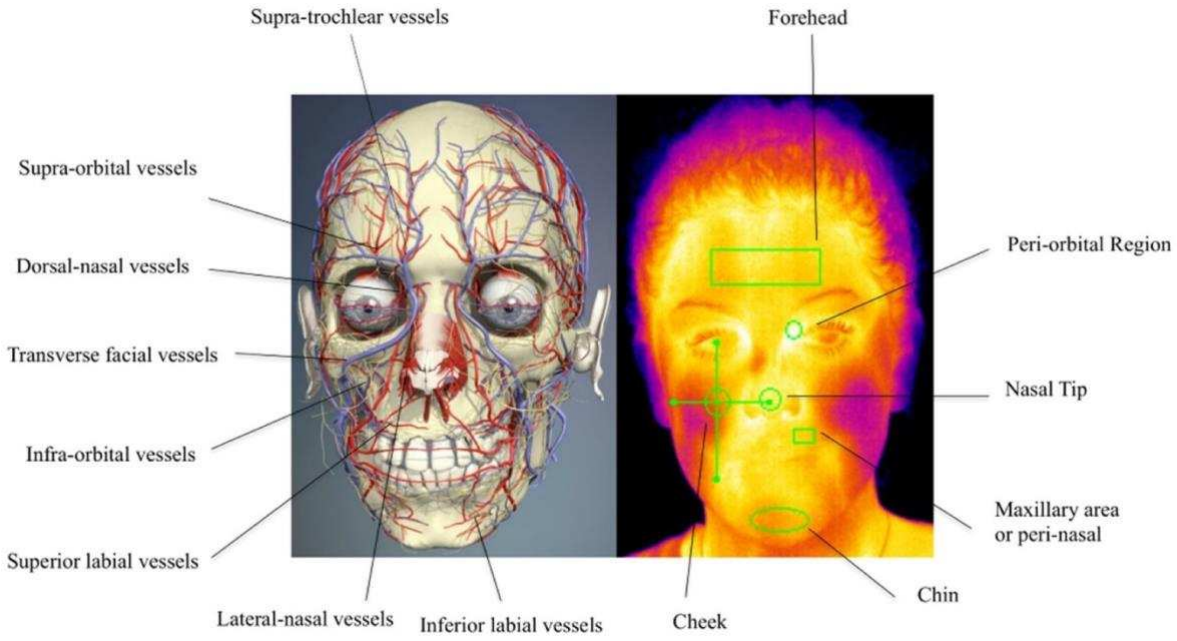

Figure 5. *The major vessel affecting the subcutaneous temperature of the face and different thermal Region of Interest (ROIs) (Berkovitz, Kirsch, Moxham, Alusi, & Cheesman, 2013).*

One study examined changes in forehead and nose temperature to estimate the cognitive load of participants during different cognitive tasks (e.g., Stroop test). It has been observed that the increased cognitive task difficulty led to significant increases in the forehead temperature and decreases in nose temperature (Abdelrahman et al., 2017). This technique has already proven useful in the context of driving, both in real and simulated environments, to identify changes in driver state due to fatigue and stress conditions. In a simulated driving study, nasal skin temperature was monitored to assess changes in arousal levels during a 2-hour driving session. It was observed that the nasal skin temperature changed as a function of driving time, i.e. it increased for the first 75 minutes of driving, then began to decrease, but this decrease gradually normalized as time passed (Diaz-Piedra et al., 2019). Tashakori and colleagues measured the forehead and cheek temperature to detect drivers' drowsiness. After simulated driving task, the temperature gradient of the skin of the forehead and cheeks decreased (Tashakori et al., 2022). Based on past research documented in

the literature, skin temperature and TII have been demonstrated to provide effective measures for the assessment of driver states.

1.3 New perspective technologies to improve driving safety

Improving the quality of driving, safety and security of drivers and passengers is a topic of great interest and is now being studied by both academia and industrial manufacturers. The recent growth in technology has made it possible to develop various strategies to assist drivers and reduce the risk of car accidents. These include the development of environmental and road technologies, driving assistance technologies (e.g., ADAS), the design of cars with different levels of driving automation, and even autonomous driving. Focusing on traffic and road infrastructure engineering strategies, the introduction of Smart on-Road Technologies (SRT) may represent a device to limit the driver's errors while driving. The SRT are installation on the road, with which drivers interact passively, designed to reduce road accidents (Figure 6). Musical road technology, smart crosswalks, photoluminescent road markings are different types of SRT, each of which aims to improve driving behaviour by enhancing the driver's attention and alertness (for a recent review, see Angioi et al., 2023). Generally, road markings delineate the traffic surface by using lines, text, and symbols to provide visual guidance information for road users (Babić et al., 2016). For instance, the application of the SRT in road pavement (i.e., photoluminescent technology) allows to support driver's vision in low-light traffic scenarios, promoting visibility of the roadway trajectory (Zhu et al., 2021). Comparing to the conventional markings, less variance in speed was observed in the SRT condition, suggesting a positive effect on drivers' control of vehicle speed (Shahar et al., 2018). Therefore, the application of smart road technologies could promote driving vigilance, contrasts fatigue and limit its negative effects on driving behaviour and performance. Moreover, the technological progress has opened up new possibilities with respect to traditional manual driving, especially in term of the

Figure 6. *An example of Smart on-Road markings*

degree of control and automation of driving. The autonomous drive has been defined as the ability of a vehicle to drive partially or completely by itself, with little or no human intervention. The Society of Automotive Engineers (SAE) classified levels of driving automation into six numerical categories which ranges from completely no automation to a fully automatic vehicle (Figure 7) (SAE, 2019). Among these six levels, a distinction must be made between assisted driving and autonomous driving. Driving assistance, such as on-board Advanced Driver-Assistance Systems (ADAS), includes those systems that allow the car to intervene in certain driving situations in order to assist the driver. In detail, examples of ADAS mechanisms equipping modern vehicles are Anti-lock Braking System (ABS), Adaptive Cruise Control (ACC), Electronic Stability Control (ESC), Lane Departure Warning System (LDWS), Forward Collision Warnings (FCW), Traffic Sign Recognition (TSR), automotive night vision, collision avoidance systems, and driver drowsiness detection (Ziebinski et al., 2017; Satoh et al., 1983; Kortil et al., 2016; Luo et al., 2018; Martinelli et al., 1999). Then, as a common objective, all these ADAS can actively help to avoid potentially dangerous situations by reducing the risk of

accidents, but they are not active driving systems because they only function in response to specific inputs. Therefore, in assisted driving, the car only intervenes to support the driver, whereas in autonomous driving the vehicle is ultimately responsible for handling of driving situations. Thus, levels 0 and 1 represent assisted driving situations, level 2 is the preamble to automation, while levels 3, 4 and 5 are autonomous driving. Hence, investment by the automotive industry on research and production of these vehicles could in future reduce the negative effects of driving, such as under fatigue driver conditions.

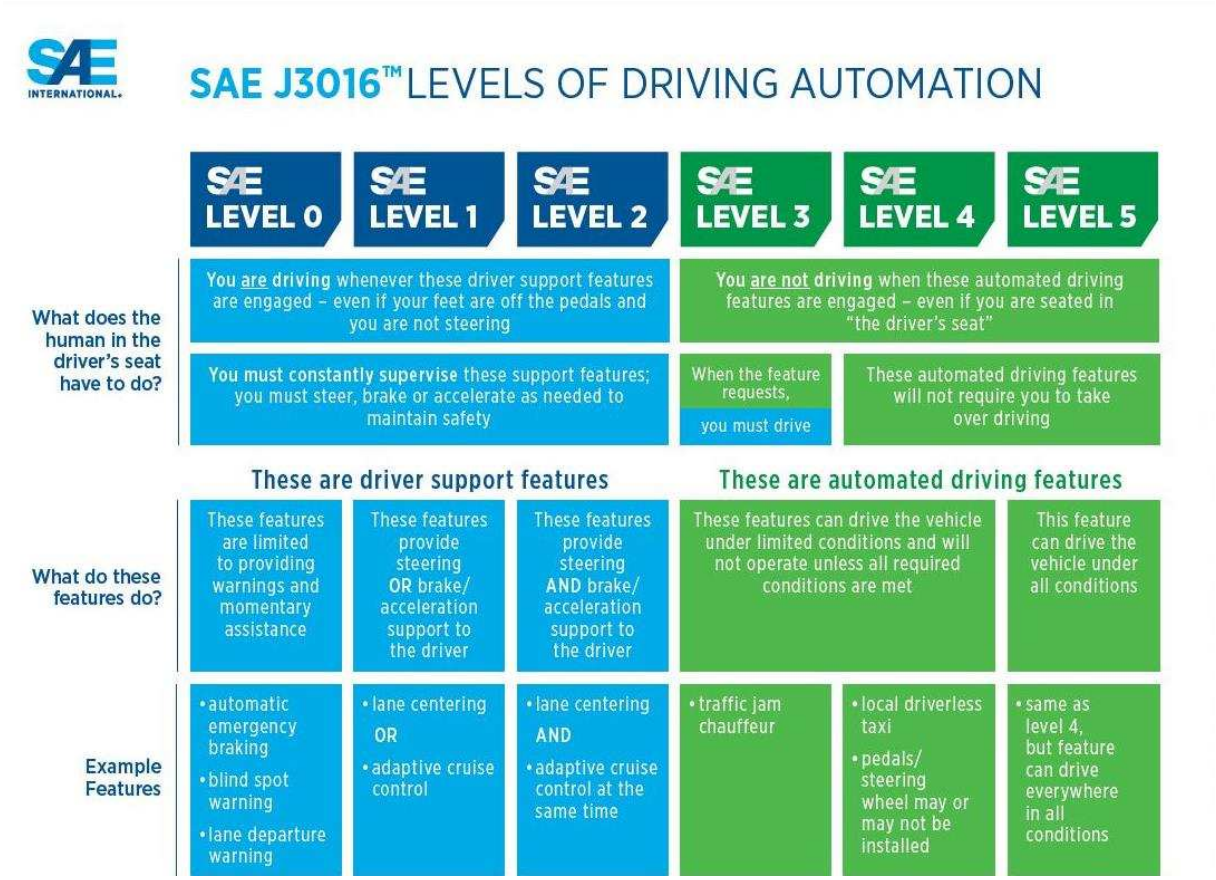

Figure 7. *Sae classification of driving automation*

Lastly, the ubiquitous diffusion of the Internet of Things (IoT) paradigm has influenced and changed our lifestyle, thanks to the ability to interconnect heterogeneous devices (such as sensors, actuators, or more in general, smart objects), combining different technologies and communication protocols

to build services for end users. Due to this heterogeneity, IoT applications are numerous, and one of the most relevant is related to the automotive industry, with the aim of gaining a better understanding of the driver-vehicle system as a whole, thus improving safety and driving quality. In terms of driver assistance systems, most existing ADAS do not take into account all aspects of the driver, such as his or her psycho-physiological state (or do not consider it at all). Comprehensive knowledge and monitoring of the driver's state would make it possible to detect whether the driver is physically, emotionally and physiologically capable of driving the vehicle and to effectively communicate ADAS decisions to the driver or to act directly on the vehicle. Although a monitoring system with these characteristics is very challenging to obtain, an ADAS informed about of driver's psycho-physiological state could take more contextualized actions, implementing more complex decisions compatible with the driver possible reactions (Davoli et al., 2016, Davoli et al., 2022). Therefore, the design and the implementation of an advance in-vehicle Driver Monitoring System (DMS) (Figure 8) could be able to collect and jointly process physiological data (see appendix, Mattioli et al., 2024).

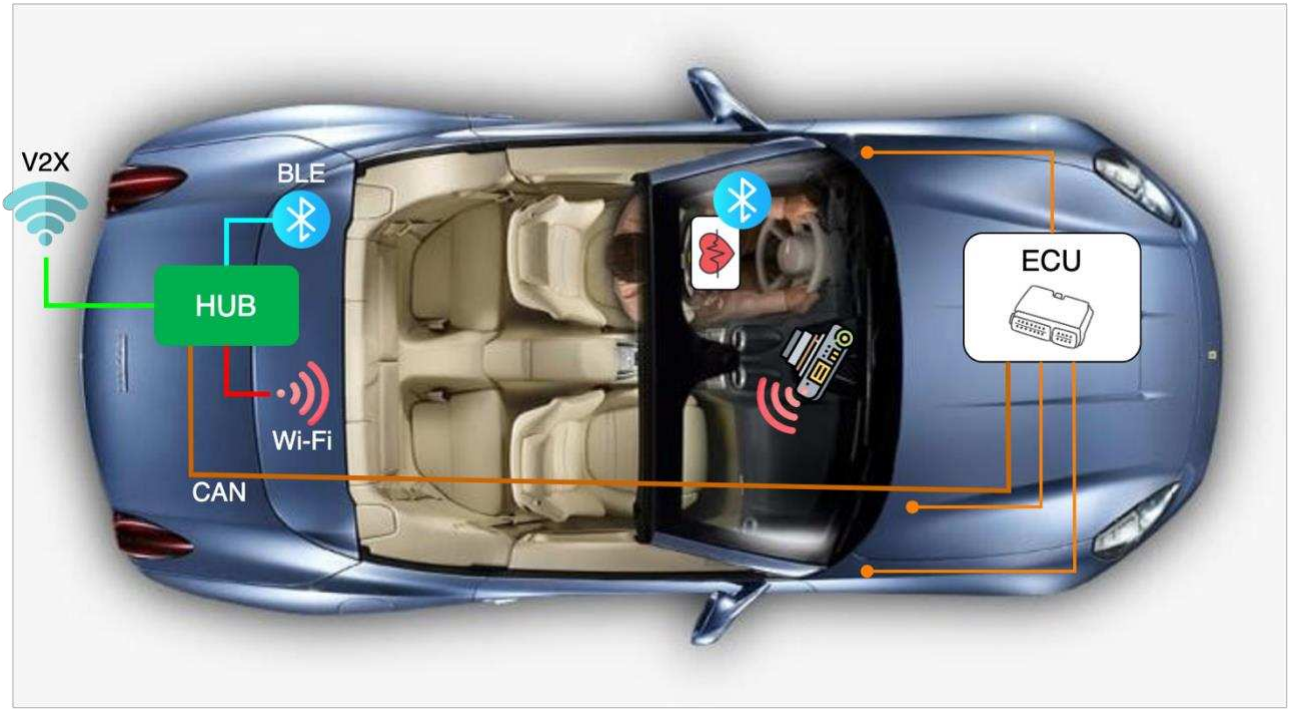

***Figure 8**. DMS based on IoT-oriented technologies proposed by Mattioli and colleagues (2024)*

1.4 General aims

The present project sought to investigate in depth a complex and dynamic every day activity as driving a vehicle. In light of the considerable number of road accidents, there has been a notable increase in interest over recent years to gain a deeper understanding of the factors that can impair driving efficiency and to develop strategies to support drivers and enhance road safety. As illustrated above, several factors influence driving behavior and risk on the road, including mental and emotional conditions (e.g. mental workload, fatigue, sleep quality, stress), external elements (such as road type and weather), as well as socio-demographic characteristics (e.g., sex, age, driving experience) may explain the heterogeneity in operating the vehicle. These factors can exacerbate a driver's discomfort and interfere with safe driving. Under mental conditions of both high and low arousal state, a series of neurovegetative responses, mediated by the autonomic nervous system (ANS), are elicited and can be detected by non-invasive peripheral measurement tools such as heart rate variability and infrared thermography. Psycho-physiological methods, already validated in various research and clinical fields, could be applied to driving activity research to enhance our understanding of driver behaviour. Thus, the main goal of this thesis was to explore and monitor the driver's physiological state in both real and simulated driving contexts and to examine the effects of various interfering factors, both environmental and human, that can potentially cause changes in driving behaviour and alter the driver's psychophysiological state. In other words, we examined whether and how human factors, such as the driver's perceived levels of stress, mental workload and fatigue, or environmental factors (e.g., road type), could modulate his/her autonomic response while driving. This thesis comprises three studies, each of which sought to contribute to the existing body of knowledge on the extent to which and the manner in which these factors can influence the driver's psycho-physiological state.

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CHAPTER 2. – Study 1: Monitoring the psychophysiological state of car drivers in real road driving context

2.1 Introduction

Every day, while travelling by car, each one is exposed to different events and situations, which can have a certain impact on the driver's psycho-physiological state. External factors such as road design (motorways vs. rural roads vs. city roads, etc.), road layout (straight vs. curves, steep road vs. downhill road, etc.), traffic flow (high vs. low) and weather can influence and increase driving-related stress (Dwight and David, 1997; Hill and Boyle 2007, Healey and Picard, 2005; Westerink et al. 2008). To this end, literature studies examined the relationship between traffic conditions and stress levels and, as expected, they found that driving stress is greater in high traffic jam areas rather than in low congestion areas. Moreover, it has been observed that these stressful situations may have a certain impact in altering the driver's physiological state. For instance, an increase in cardiac autonomic activation was observed while driving in an urban context compared to driving on highways (Tavakoli et al., 2020; Riener et al., 2009). The cognitive demands in the urban context are greater than in the highway context, the driver must pay attention to changing traffic lights, crosswalks, and everything is more unpredictable. Indeed, challenging or unexpected traffic situations, which can result in frustration and anger, have been shown to be associated with unsafe, risky and aggressive driving behaviours (Lee and Winston, 2016). To study the effects of stress on driving, several methods have been applied to manipulate emotional state and mental workload (Gilet, 2008; Fairclough and Spiridon, 2012; Stephens and Groeger, 2014). In high cognitive driver workload state, an increased HR and decreased HRV were observed (Heine et al., 2017), and these findings were also observed in an on real road study (Mehler et al., 2012), where participants performed the n-back task while driving following the directions of the experimenter. In addition, driver's demographical characteristics (such as sex, age, and accident history) have been studied in

relation to driving behaviours. Sex and age differences were observed in risky driving behaviour. Most studies suggest that male drivers drive more aggressively than female drivers, increasing the risk of crashing (Rhodes and Pivik, 2011). Moreover, various studies have shown that sex and age are demographic factors correlated with the Manchester Driving Behaviour Questionnaire (DBQ), a widely used measure of aberrant driving behaviour (Reason et al., 1990). Male drivers exhibit more violations and lapses than women drivers (Rezapur-Shahkolai et al., 2020; Cordellieri et al., 2016). However, female drivers make more errors than male drivers (De Winter and Dodou, 2010). In addition, young drivers are more likely to experience accidents than older drivers. This may be caused by the fact that young drivers tend to overestimate their driving ability (Singh and Kathuria, 2021). It has been observed that young drivers (19–25 years) exhibited more aberrant driving habits compared to middle-aged drivers (26–59 years) (Arafa et al., 2020). Apart from sex and age, driving experience has been identified as a risk factor for traffic accidents. Indeed, aberrant driving behaviours and traffic violations are higher within the first three years after licensure (Roman et al., 2015). Due to the high number of road accidents, it is important to gather as much information as possible on the causes and consequences that may reduce alertness at the wheel. In order to plan and develop support strategies while driving, it is functional to monitor the psychophysiological state under conditions that could lead to its alteration. As illustrated, both environmental and human characteristics must be considered when investigating the issue of safety behind the wheel. Gathering information about the driver's psychophysiological state can be useful in developing systems that promote safe driving. Few studies have monitored cardiovascular autonomic activity related to stress during a real driving route, especially with a passenger in the vehicle. Most of these studies have adopted the dual-task technique to induce workload in the driver (e.g., tasks involving working memory), which are not strictly associated with driving daily tasks. Furthermore, there is

little evidence on sex and driving experience differences in cardiovascular autonomic response during driving test.

2.2 Aims

On the basis of the premises above, the present study aimed at monitoring the driver's psychophysiological state during a real road driving, as this experimental approach provides more ecological information than simulated driving conditions. Cardiac autonomic activity was monitored assuming variations depending on the driving context (ring-road vs. urban driving) and the induction of psychosocial stress during urban driving (namely, unknown driving route and experimenter as evaluator passenger). We hypothesised an increase in the stress response as a function of unpredictability of the route and the exposure to comments on the participant's driving style by the passenger researcher. Moreover, we aimed at exploring the potential sex and driving experience differences in drivers' psychophysiological outcomes. Lastly, we examined correlations between cardiac autonomic activation while driving and psychological factors such as stress and anxiety symptoms.

2.3 Methods

Participants

Forty volunteer subjects from the University of Parma (Italy) community were recruited in the study, and all signed the informed consent before starting the experiment. Eligibility criteria included being in good health (no history of cardiovascular or mental disorders), having held a driver's license for at least one year, and owning a car. A sample size calculation was not deemed necessary because of the exploratory nature of the study. Due to technical problems, data from two participants were excluded from the overall analysis. The final sample consisted of thirty-eight healthy drivers (20 males, 18 females, mean age: 26.21 ± .72 years, age range: 20-38 years). All the participants had held a driver's license for at least one year, on average for 7.23 years (Standard Error, SE=.76, range 1-20), among which 65.8% had driven more than 10.000 km per year.

The median split of years of driving experience (calculated from the year when the driving license was obtained) was used to divide the sample in two groups, namely, novice drivers (less than 5 years of experience) and expert drivers (more than 5 years of driving license). The study conformed to the Declaration of Helsinki and the protocol (Research Ethics Board – REB, prot. n. 85795) was approved by the Ethical Committee of the University of Parma, Italy.

Experimental design

This study was carried out in Parma, Italy, with every driving test taking place in the time range 4 PM–6 PM, from April 2022 to May 2023. Each subject completed 25 km of real road driving in his/her own vehicle with an experimenter as a passenger. The experimental procedure included six different phases (see Figure 1) associated with different amount of workload demands due to various external factors, i.e., road type and co-driving. Drivers were recommended to abstain from caffeine and nicotine consumption for at least two hours prior to the driving task, as these variables may have

transient effects on cardiovascular measurements (Laborde et al., 2017). Upon their arrival to the laboratory, each participant was equipped with an Equivital EQ02 Life Monitor (Equivital EQ02, Hidalgo, UK) wearable bodice allowing real-time acquisition of ECG signals. Subsequently, a series of socio-demographic, usual driving behaviour and dispositional scales were administered (see below *Psychometric measurements*) and the first driving phase was illustrated, particularly the first section of the ring road, whereas the remaining route remained unknown. In the meantime, one of the experimenters made the car ready for the task, setting up a GoPro camera (GoPro, Inc., San Mateo, USA) near the headrest and waiting for the driver while sitting on the back seat. The GoPro camera was useful for recording information about the external environment while driving. Baseline tracings were recorded once the experimental driver took a seat in the vehicle. After 10 min of baseline recording, the driving session began with the subject following the route described above, with the experimenter acting as a silent passenger. In the following 15-min of urban driving route, the experimenter gave road indications to the driver and, only in the 5-min stress phase, added standardized comments on his/her driving style (e.g. “Watch out for pedestrian crossing; “Remember to put on your indicator when you have to turn”). Then, the subject returned to the ring road and the experimenter remained again silent. Finally, the driver parked the car and remained in the vehicle for 10 min (recovery phase). At the end of the driving session, the driver returned to the laboratory and completed the psychometric tests. The driving route is described in more details in Fig 2.

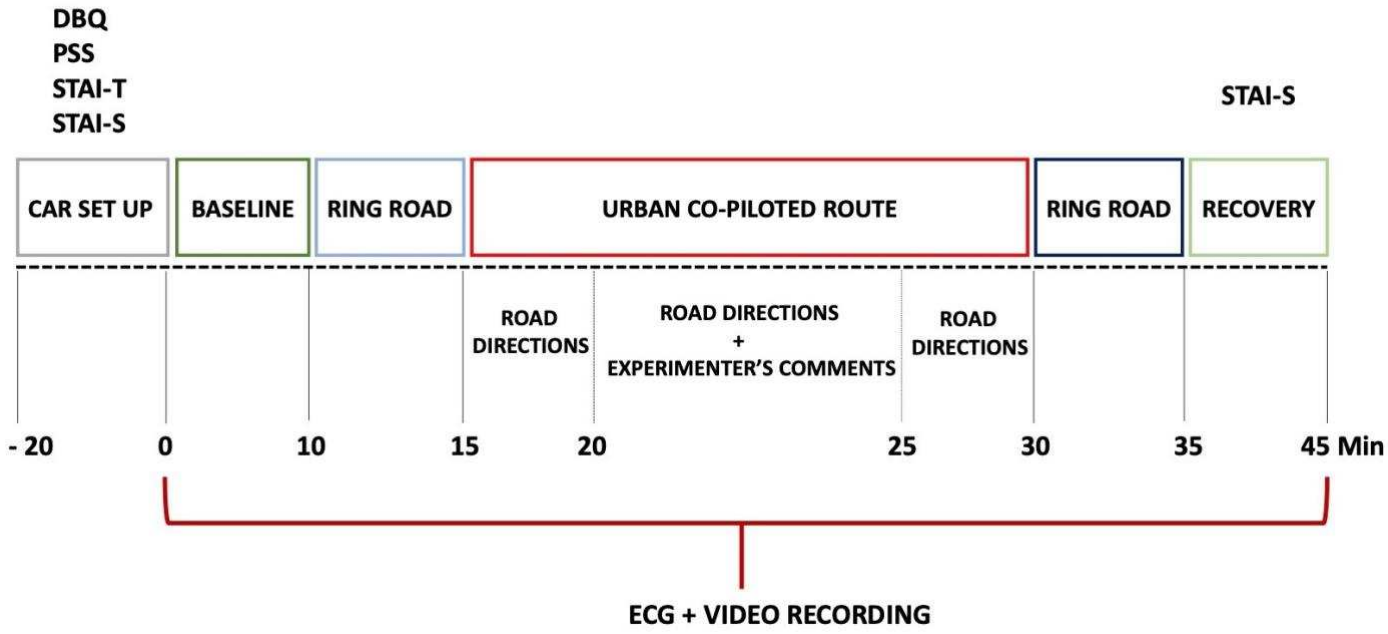
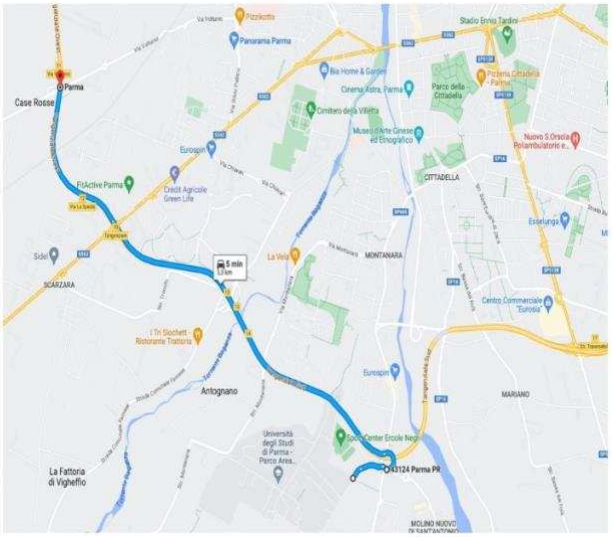
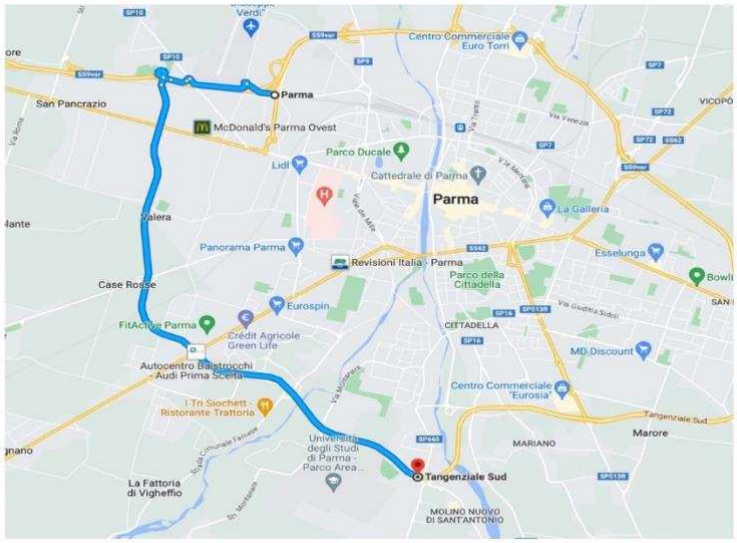


Figure 1. *Timeline of the experimental procedure. Abbreviations: DBQ = Driving Behaviour Questionnaire; PSS = Perceived Stress Scale; STAI-T = State-Trait Anxiety Inventory, Trait version; STAI-S = State-Trait Anxiety Inventory, State version.*



a

b



c

Figure 2. *The maps of the experimental driving route (a: first route of the ring road; b: urban route; c: last route of the driving task on the ring road)*

Psychometric measurements

A driving history questionnaire was designed to collect information about the daily frequency of vehicle use, kilometres driven in the last year (i.e., less or more than 10.000 km), car crashes, and traffic law penalties in the last year.

The Italian version of the Manchester DBQ (Smorti & Guarnieri, 2016) allows the measurement of aberrant driving behaviour. The DBQ 27-item version includes the following behaviours: (1) errors (8 items), consisting in failures of planned actions (i.e., fail to notice that pedestrians are crossing when turning into a side street from a main road); (2) lapses (8 items), consisting in failures of attention and memory (i.e., attempt to drive away from the traffic lights in third gear); (3) ordinary violations (8 items), consisting in deliberate decisions to deviate from traffic safety rules (i.e., overtake a slow driver on the inside); (4) aggressive violations (3 items), consisting in deliberate actions based on negative emotions (i.e., sound your horn to indicate your annoyance to another road user). Participants were asked to indicate how often they commit each of these behaviours, on a six-point Likert scale, ranging from "never" to "nearly all the time."

The Perceived Stress Scale (PSS) is the most widely used psychological instrument for measuring the perception of stress. It is a measure of the extent to which situations in one's life are appraised as stressful (Cohen et al., 1983). Items were designed to tap how unpredictable, uncontrollable, and overloaded respondents find their lives. The 10 questions that compose the PSS are related to feelings and thoughts experienced during the last month. In each case, respondents are asked how often they felt a certain way. Scores ranging from 14 to 26 are considered "moderate perceived stress," those ranging from 27 to 40 are considered "high perceived stress."

The severity of trait anxiety was measured using the trait version of the State-Trait Anxiety Inventory (STAI) (Spielberger et al., 1970), which is a 4-point Likert scale consisting of 20 items assessing how the subject feels, regardless of the status and circumstances (i.e., "I feel secure," "I feel troubled"):

the lowest score that can be obtained is 20 and the highest is 80, with higher scores indicating higher anxiety levels. The validity of this scale has been repeatedly confirmed, with reliability coefficients ranging from .71 to .86, and internal consistency and homogeneity coefficients between .83 and .87. State anxiety was measured using the state version of the STAI (also denoted as STAI-S), which asks how respondents feel "right now" using 4-point Likert scale items that measure subjective feelings of apprehension, tension, nervousness, worry, and activation/arousal of the autonomic nervous system. The reliability coefficient is .62. The trait version of the STAI (also denoted as STAI-T) was administered once, whereas the state version was administered before and at the end of the driving task.

Heart Rate and Heart Variability Analysis

ECG signals, obtained with the EQ02 LifeMonitor sensor, were exported using the Equivital Manager software and analysed by means of the Chart5 software (ADInstruments, Sydney, Australia). Initially, each raw ECG signal was manually inspected to ensure that all R-waves were correctly detected and to exclude artifacts before further analysis. For each recording period, ECGs were split in 5-min epochs. For each epoch, HR and HRV indexes were generated. The Root Mean Square of Successive Beat-to-Beat Interval Differences (RMSSD, dimension: [ms]) is considered as a vagally-mediated index of HRV (Laborde, Mosley, & Thayer, 2017) and is less susceptible to respiratory and movement artifacts compared to the alternative frequency-domain High Frequency (HF) parameter (Hill et al., 2009).

Average HR and HRV values were calculated at each 5-min epoch. Only the first and last 5 min of recording were used for the baseline and recovery epochs, respectively. In addition, values of the Area Under the Curve (AUC, i.e., the area comprised between the response time curve and the baseline) were obtained for each autonomic parameter. Finally, delta values of HR and RMSSD

(denoted as Δ HR and Δ RMSSD) were calculated as the difference between the recovery and the last driving phase (ring road) values.

Statistical Analysis

Data are expressed as means ± SE. Statistical analyses were performed with the SPSS v.28 software package (SPSS Inc., Chicago, IL). Statistical significance was set at $p < 0.05$. The normal distribution of variables was determined using the Kolmogorov-Smirnov test.

Differences in sex and experience were analysed as potential explanatory components of psychophysiological modulation during driving.

Considering the full sample, cardiac autonomic responses to the driving task were analysed with a one-way ANOVA for repeated measures.

Differences between the sex group (male vs. female) in age, years of experience (years of driving license) and psychometric characteristics were analysed by Student's t-tests and $\chi 2$ tests. Cardiac autonomic responses to the driving task (AUC HR, AUC RMSSD, Δ HR and Δ RMSSD) were analysed by Student's t-tests.

Differences between the experience group (novice vs. expert) in sex, age and psychometric characteristics were analysed by Student's t-tests and $\chi 2$ tests. Cardiac autonomic responses to the driving task (AUC HR, AUC RMSSD, Δ HR and Δ RMSSD) were analysed by Student's t-tests.

Partial correlation analyses (controlling for sex and level of driving experience) were computed to compare psychometric characteristics to HR and HRV (i.e., AUC and Δ variations) responses to driving task.

2.4 Results

Cardiac autonomic responses to the driving task

Figure 3 shows cardiac autonomic response to the driving task for the full sample of drivers. A one-way ANOVA for repeated measure yielded a significant effect of "recording period" for HR (F=40.01, $p < .001$, $\eta_p^2 = .520$) and RMSSD (F=31.52, $p < .001$, $\eta_p^2 = .460$). Considering the full sample, HR was significantly higher during Rr1 (89.17 $\pm$ 2.41 bpm, $p < .001$), U1 (87.57 $\pm$ 2.14 bpm, $p < .001$), U2 (89.02 $\pm$ 2.09 bpm, $p < .001$), U3 (89.75 $\pm$ 2.14 bpm, $p < .001$) and Rr2 (86.28 $\pm$ 2.11 bpm, $p < .001$) compared with baseline value (80.57 $\pm$ 2.10 bpm) (Figure 3A). RMSSD values were significantly lower during Rr1 (24.94 $\pm$ 2. 04 ms, $p < .001$), U1 (27.27 $\pm$ 1.90 ms, $p < .001$), U2 (25.66 $\pm$ 1.83 ms, $p < .001$), U3 (25.00 $\pm$ 1.87 ms, $p < .001$) and Rr2 (25.80 $\pm$ 1.91 ms, $p < .001$) compared with baseline value (35.04 $\pm$ 2.13 ms) (Figure 3B).

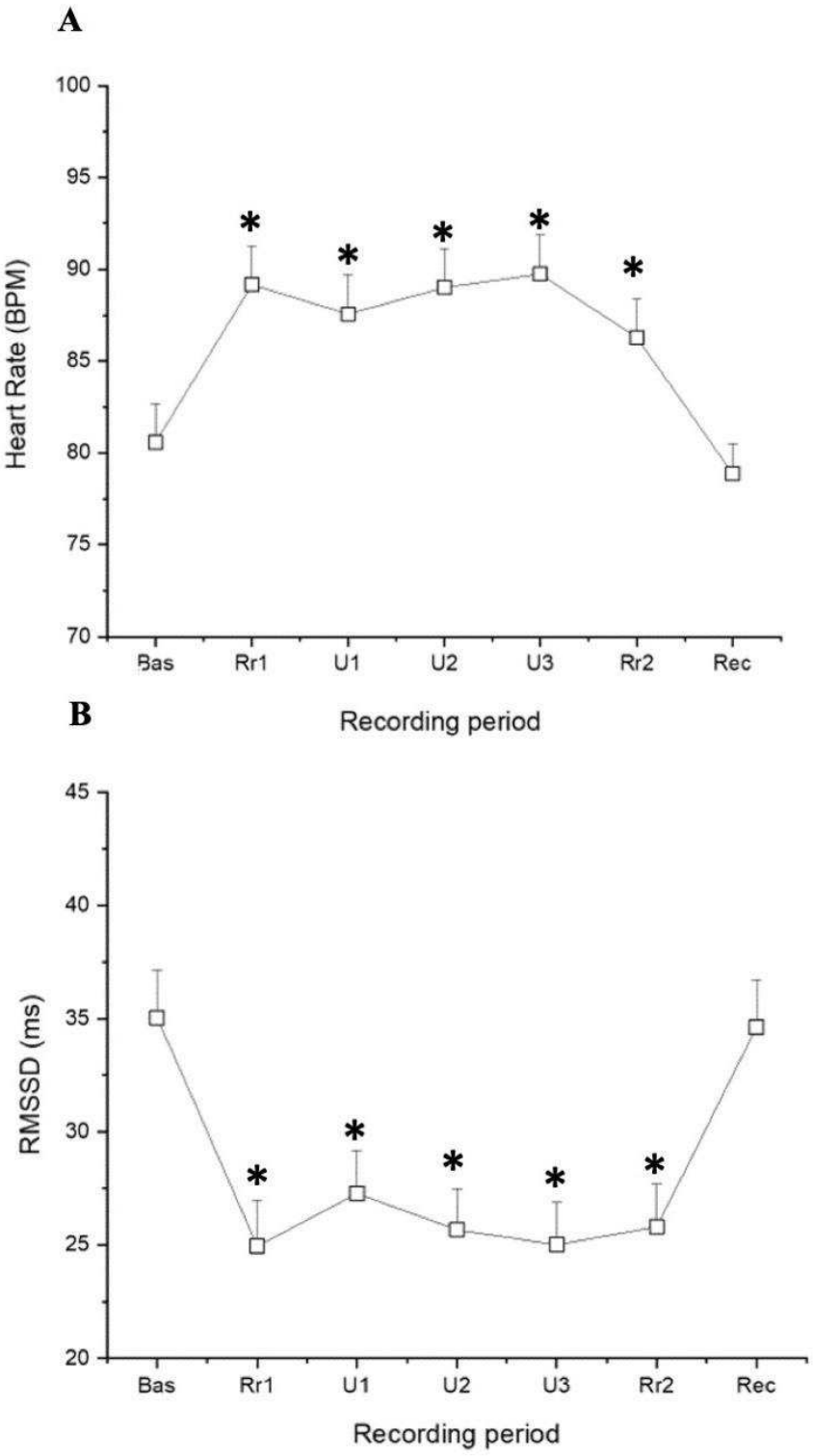


***Figure 3**. HR (A), HRV (B) responses to the driving task for the full sample of drivers (n = 38). Data are reported as mean ± standard error. Abbreviations: bas = baseline; Rr1 = ring road 1; U1 = urban 1; U2 = urban 2; U3= urban 3; Rr2 = ring road 2; Rec= recovery; RMSSD = root mean square of successive beat-to-beat interval differences. (p < .05: * = vs Bas)*

Exploring sex differences in drivers' psychophysiological outcomes

The first subdivision of the sample was done by following the criterion of sex (Female n=18, Male n=20). There were no significant age differences between women and men. Their mean ± SE age was respectively 25.83 ± .95 years and 26.55 ± 1.08 years (t=-.495, p=.62). Importantly, female and male drivers had held their driver's license, on average, since the same years [F= 6.8 ± .90 years; M= 7.6 ± 1.2 of driving license (t=. -505, p=.61)].

In Table 1 the psychometric characteristics of male and female drivers are shown. Female drivers exhibited a significantly higher predisposition to commit lapses than males, with a larger effect size. In addition, female drivers were .63 standard deviation higher in errors subscale of the DBQ, although this difference did not reach full statistical significance. Perceived stress symptoms were significantly higher in the female group, with a large effect size. No group differences were found for STAI and other DBQ scales.

Table 1. *Psychometric characteristics of male and female drivers*

	Female *(n=18)*	Male *(n=20)*	t	p	Effect size *(Cohen's d)*
DBQ (score)					
Errors	4.94 ± .90	2.85 ± .59	1.92	.063	.63
Lapses	10.88 ± 1.19	7.35 ± .98	2.28	.029	.74
Ordinary violations	8.72 ± 1.03	10.25 ± 1.01	-1.05	.300	-.34
Aggressive violations	2.88 ± .73	2.15 ± .49	.83	.411	.27
PSS (score)					
Perceived stress	19.83 ± 1.25	15.65 ± 1.37	2.24	.031	.72
STAI (score)					
Trait anxiety	44.66 ± 2.22	41.25 ± 1.93	1.15	.255	.37
State anxiety (pre-driving task)	36.11 ± 2.38	34.65 ± 1.72	.49	.622	.16
State anxiety (post-driving task)	36.61 ± 2.11	34.75 ± 1.37	.73	.467	.24

Data are reported as mean ± SE.
Abbreviations: DBQ Driving behaviour questionnaire, PSS Perceived stress scale, STAI State-trait anxiety inventory

Table 2 shows cardiac autonomic responses to the driving task of male and female drivers. Student's t-tests showed no significant differences in the AUC and Δ values of HR and RMSSD between male and female drivers. Female were .57 standard deviation lower in the AUC of HR, although this difference did not reach statistical significance.

Table 2. *Sex differences in arousal and deactivation during driving*

	Female *(n=18)*	**Male *(n=20)***	**t**	**p**	**Effect size** ***(Cohen's d)***
AUC HR	98.03 ± 24.83	162.68 ± 26.54	-1.77	.08	-.57
AUC RMSSD	-166.41 ± 36.09	-161.60± 29.33	-.103	.91	-.03
ΔHR	-7.04 ±1.39	-7.71 ± 1.82	.29	.77	.09
ΔRMSSD	-10.27 ± 1.61	-7.51 ± 2.14	-1.04	.30	-.34

Data are reported as mean ± SE.
Abbreviations: AUC HR area under the curve of HR, AUC RMSSD area under the curve of root mean square of successive beat-to-beat interval differences, Δ HR delta of HR and Δ RMSSD delta of root mean square of successive beat-to-beat interval differences (Δ difference between the recovery and the last driving phase (ring road) values).

Exploring driving experience differences in drivers' psychophysiological outcomes

Following the criterion of driving experience, novices (drivers with less than 5 years of license) were 15 and experts (drivers with more than 5 years of license) were 23. There were significant differences in age between novice and expert drivers (t= -4.67, p = <.01). Their mean ± SE age was respectively 22.86 $\pm$ .48 years and 28.39 $\pm$ .89 years. There were no differences in the proportion of males and females (χ^2 =.35, p=.55).

Table 3 shows psychometric characteristics of novice and expert drivers. Novice drivers exhibited a significantly higher predisposition to commit lapses than experts, with a large effect size. No group differences were found for the other psychometric characteristics.

Table 3. *Psychometric characteristics of novice and expert drivers*

	Novice *(n=15)*	Expert *(n=23)*	t	p	Effect size *(Cohen's d)*
DBQ (score)					
Errors	4.93 ± 1.15	3.13 ±.48	1.63	.112	.54
Lapses	11.26 ± 1.47	7.56 ± .82	2.19	.039	.78
Ordinary violations	10.20 ± 1.27	9.08 ± .87	.71	.478	.24
Aggressive violations	3 ± .63	2.17 ± .58	.95	.347	.30
PSS (score)					
Perceived stress	18.40 ± 1.54	17.13 ± 1.29	.63	.533	.20
STAI (score)					
Trait anxiety	42.33 ± 2.33	43.21 ± 1.93	-.29	.773	-.09
State anxiety (pre-driving task)	33.46 ± 2.06	36.56 ± 1.93	-1.09	.281	-.35
State anxiety (post-driving task)	34.46 ± 1.91	36.39 ± 1.61	-.76	.448	-.25

Data are reported as mean ± standard error.
Abbreviations: DBQ Driving behaviour questionnaire, PSS Perceived stress scale, STAI State-trait anxiety inventor

Table 4 shows cardiac autonomic responses to the driving task of novice and expert drivers. Student's t-tests showed no significant differences in the AUC and Δ values of HR and RMSSD between novice and expert drivers.

Table 4. *Driving experience differences in arousal and deactivation during driving*

	Novice *(n=15)*	**Expert *(n=23)***	**t**	**p**	**Effect size** *(Cohen's d)*
AUC HR	108.44 ± 25.07	147.45 ±26.30	-1.07	.290	-.33
AUC RMSSD	-147.77 ± 35.12	-174.38 ±30.15	.57	.57	.18
ΔHR	-8.54 ± 2.37	-6.65 ± 1.13	-.71	.48	-.26
ΔRMSSD	-10.06 ± 2.58	-8.01 ± 1.38	-.69	.49	-.25

Data are reported as mean ± standard error.
Abbreviations: AUC HR area under the curve of HR, AUC RMSSD area under the curve of root mean square of successive beat-to-beat interval differences, Δ HR delta of HR and Δ RMSSD delta of root mean square of successive beat-to-beat interval differences (Δ difference between the recovery and the last driving phase (ring road) values).

Correlations between cardiac autonomic driving responses and psychometric characteristics

No significant correlations were found between HR and RMSSD (AUC and Δ values) responses to the driving task and psychometric characteristics (as shown in Table 5). On the other hand, we found significant positive correlations between trait anxiety scores, stress-related symptoms (PSS) and most aberrant driving behaviours (DBQ), controlling for sex and driving experience.

Table 5. *Partial correlations (controlling for sex and driving experience) among psychometric characteristics and HRV responses to driving task for the full sample of drivers (n = 38)*

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.Errors (DBQ)	r	-											
	p	-											
2.Lapses (DBQ)	r	.627	-										
	p	<.001	-										
3.Ordinary Violations (DBQ)	r	.509	.378	-									
	p	.002	.023	-									
4.Aggressive Violations (DBQ)	r	.430	.229	.382	-								
	p	.009	.179	.021	-								
5.PSS	r	.436	.513	.329	.386	-							
	p	.008	<.001	.050	.020	-							
6.STAI-T	r	.444	.500	.258	.418	.714	-						
	p	.007	.002	.128	.011	<.001	-						
7. STAI-S (pre-driving)	r	.400	.231	.075	.298	.540	.683	-					
	p	.016	.175	.663	.077	<.001	<.001	-					
8.STAI-S (post-driving)	r	.426	.453	.118	.350	.538	.791	.611	-				
	p	.010	.006	.492	.036	<.001	<.001	<.001	-				
9.AUC HR	r	-.275	-171	-.042	-.258	-.027	-.096	-.185	-.114	-			
	p	.105	.318	.808	.129	.876	.577	.280	.508	-			
10.AUC RMSSD	r	.201	.105	.019	.200	-.064	-.005	.047	.104	-.774	-		
	p	.240	.542	.914	.242	.712	.975	.787	.545	<.001	-		
11. Δ HR	r	.071	.139	-.207	.091	.037	.134	.256	.279	.011	.036	-	
	p	.680	.420	.226	.599	.831	.437	.132	.099	.949	.835	-	
12. Δ RMSSD	r	.171	.050	-.111	-.073	.091	-.097	.112	.049	-.235	.062	.484	-
	p	.318	.772	.519	.673	.596	.573	.515	.777	.168	.721	.003	-

2.5 Discussion

Driving a vehicle is a complex behaviour which requires an optimal psychophysiological state in order to perform the task safely. Due to the high number of road deaths and traffic injuries, especially among young people, road safety has become an international concern. The development of new technologies and the identification of the human factors that affect driving behaviour could improve driver well-being (Davoli et al., 2022; Mattioli et al., 2024). In order to acquire information about driver's psychophysiological response in ecological contexts, we investigated cardiac autonomic modulation during a real road driving by means of HRV measurements. In this study, each driving test was performed on a sunny day, as it was observed that weather affects the stress behind the wheel (Hill and Boyle, 2007). The driving experimental procedure included both urban and extra-urban road (ring road) in order to examine possible physiological variations depending on road and traffic flow conditions. Considering the full sample of our research, HR significantly increased and HRV (RMSSD) significantly decreased compared to baseline conditions, with such effects persisting throughout the driving task. Specifically, we observed a sharp change in HRV once participants began driving and this finding is in line with previous researches. Lee et al. (2007) studied the relationship between HRV and a stressful driving situation (i.e., different road conditions) in real roads. Compared to baseline values, they found an increase in HR when participants started the driving task, although no differences in autonomic response were found between road type conditions. Similarly, our results showed significant overall autonomic activation due to driving, regardless of the amount of traffic flow (i.e., ring road vs. urban road). However, some studies have demonstrated that a higher traffic density could modulate the perception of workload and the driver's physiological response. Bitkina et al. (2019) have quantified electrodermal activity under traffic conditions and different road types in ecological conditions. It emerged that city driving was more stressful than highway driving. Tavakoli et al. (2020) applied HRV analysis to

detect stress response in different environmental conditions. A decrease in HRV (RMSSD) was observed during urban driving. Contrarily, in a driving simulation study, Shakouri et al. (2018) found no variation in HRV indexes as a function of higher traffic density while driving. Therefore, there are still uncertainties and inconsistencies concerning the impact of varying environmental conditions (e.g., urban vs. highway/ring road) on autonomic neural modulation while driving. This may be dependent on the nature of the experimental settings, particularly if the research is being carried out in a naturalistic context. The geographical location of the driving task could make a difference (i.e., metropolitan city, dangerous road conditions). In other words, the experimental route used in our study may have not been sufficiently stressful to elicit a larger physiological response – despite city driving was included in the experimental procedure. In any case, it was important to examine the psychophysiological state of the driver in an ecological context, as we were interested in studying his behaviour in natural conditions, as close to everyday life as possible. Moreover, the psychophysiological response of the driver could be altered by the presence of an experimenter-judge in the vehicle as an additional workload factor. Several studies have adopted dual-tasks technique to induce workload in the driver. For instance, the participant carries out the driving task and simultaneously performs a cognitive task involving working memory (e.g., n-back task). It has been observed that dual-task can modulate the driver's cardiac autonomic response (Brookhuis and De Waard, 2010; Lenneman et al., 2009; Mehler et al., 2012; Heine et al., 2017). However, the present study aimed at testing an ecological workload induction method, which simulated a naturalistic driving stressful situation. The psychosocial stress here induced consisted in the presence of an experimenter (as examiner) and the unpredictability of the driving route (unknown urban route). We expected more significant HR increase and HRV reduction, due to these two stress factors, during U2 and U3 phases (*see the experimental procedure*). Conversely, our results did not support this hypothesis: no further increase in arousal was observed during psychosocial stress

phases (U2 and U3 phases). This may be due to the fact that drivers' behaviour and psychophysiological responses are influenced by their personality and the conditions of the experimental test. Indeed, driving is a complex activity that can be influenced simultaneously by several factors, not only those due to the environment, but also those related to individual characteristics. In other words, driving in an urban context was a task that required attentional resources, and it may be that the driver did not beware to the experimenter's comments, but only to road directions. Additionally, no changes in state anxiety levels (STAI-S) were observed between before and after the driving task, suggesting that the stress induction protocol did not seem to add significant pressure to the driver. However, our findings suggest that the overall driving task produced a notable impact on cardiac autonomic neural modulation. Furthermore, sex and driving experience have been considered as a modulating factor in driving behaviour (Montgomery et al., 2014; Cordellieri et al., 2016), but few studies have investigated psychophysiological differences. We examined these variables as potential modulatory components for cardiac autonomic responses during driving. Female drivers seemed to exhibit somewhat lower values of HR overall responsivity. Our results are not completely in line with previous research, which observed lower HRV values in female drivers. Miller and Boyle (2015) evaluated stress response in drivers by manipulating environmental conditions (tunnel presence) in real road itinerary. Females had significantly lower HRV values of the standard deviation between NN intervals, SDNN, and appeared more stressed than males. In a driving simulation study, female participants showed lower HRV values and significantly higher speed in driving behaviour than males (Arca et al., 2022). Moreover, no differences in autonomic response emerged when comparing driving experience groups.

In our study, we also aimed to examine the pre-existing psychometric characteristics of the drivers as possible explanatory factors for differences in driving behaviour. We pursued the goal as a function of sex and driving experience. Regardless of the experimental task, we found that the level

of perceived stress in the last month was significantly higher for female drivers than for male drivers. Our results are in line with existing literature, where women reported higher levels of PSS scores. In other words, women were more susceptible to experiencing stress than men (Graves et al., 2021; Costa et al., 2021). We were also interested in verifying the habitual risky driving style of the participants through the DBQ. Our female participants exhibited significantly higher levels of lapses in DBQ scale than male drivers. Similarly, in the study by Domnez et al. (2017), higher scores for lapses and errors were recorded in females than in males. Lajunen et al. (2022) found that women committed more lapses than men, but less aggressive and ordinary violations. Conversely, in other studies it has been observed that female exhibit less violations and lapses than men drivers (e.g., in Rezapur-Shahkolai et al., 2020).

In our study, when comparing driving experience groups, there was only one significant difference observed in the DBQ lapses scale: novice drivers were more prone to commit lapses than expert drivers. No significant correlations were found between cardiac autonomic activation and deactivation while driving (HR and RMSSD) and psychometric and driving behaviour characteristics. On the other hand, our analyses showed significant positive correlations between anxiety/stress symptoms and aberrant driving behaviour: higher levels of anxiety/stress symptoms were associated with a higher tendency to commit errors and violations. These results suggest the relevance of considering the psychological state of drivers when studying their behaviour and implementing strategies to improve driving performance.

2.6 Conclusions

Road safety is an international concern and the development of human-vehicle interaction systems is the goal of current and future research for several industrial companies and academic institutions to reduce road accidents. In order to develop effective solutions for drivers, it is important to recognize which factors can reduce the ability to drive safely. Appropriate investigations could reveal the factors which affect the driving behaviour and how drivers respond psychophysiologically to these factors. The main purpose of this work was to monitor autonomic of drivers during real driving, which included exposure to several external stressors, road type conditions (city and ring-road driving) and the presence of an experimenter as navigator and evaluator. HRV analysis revealed significant overall autonomic activation while driving, independent from the exposure to external stressors, sex, driving experience and habitual driving behaviours. A significant positive correlation emerged between anxiety-stress symptoms and aberrant driving behaviour. In summary, our results suggest that the overall driving task produced a notable impact on cardiac autonomic neural modulation. This result could be explained by the nature of the driving activity, which itself requires cognitive, attentional and physical resources. Study limitations included collecting data from a small sample size, thereby limiting our ability to find associations between individual characteristics and cardiac autonomic responses. Further investigations with larger sample sizes could reveal an association between sex/driving experience and cardiac autonomic activation during driving, which did not emerge in this pilot study. In the future, it would be useful to investigate the driver's psycho-physiological state in relation to his/her driving behaviour during the task, by retrieving data from the vehicle (e.g. vehicle speed, distance from other vehicles, lateral position) and correlating them with cardiac autonomic activation and psychometric characteristics.

In conclusion, our findings add to the current literature by examining cardiac autonomic activity while driving in an ecological context and underline the importance of taking into account variables such as sex, driving experience and personality characteristics.

Understanding the factors that influence driving performance and modulate the resulting physiological response could provide a springboard for practical applications, such as the development of human-vehicle interaction monitoring systems for optimal psychophysiological arousal while driving.

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CHAPTER 3. – Study 2: Physiological monitoring of drivers' mental workload due to distraction factors in a simulated driving environment

3.1 Introduction

One of the main causes of road accidents is distracted driving. Driver distraction is commonly described as “a diversion of attention from driving, because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces the driver’s awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near crashes, or crashes” (Regan et al., 2008). More specifically, driver distraction involves a secondary task, distracting driver attention from the primary driving task (Papantoniou et al.,2017). For instance, sources of driving distractions include interaction with technologies (e.g., mobile phones, iPods, DVD players, navigation systems, e-mail systems, radios, and CD players) and performing daily activities (e.g. eating, drinking, smoking, reading, writing, picking up objects, grooming and conversing with passengers) (Regan and Oviedo-Trespalacios, 2022). These distracting factors can increase the workload of the driver and lead to risks for the driver and other road users. Several studies have analysed the effect of distraction on mental workload and driving performance. Liang and colleagues used a driving simulator and eye-tracking technology to assess the impact of visual distraction on driving performance and mental workload. The results showed that distraction leads to a decrease in driving control and an increase in mental workload, characterized by poorer vehicle handling and longer reaction times (Liang et al., 2024). The evaluation of the effects of distractive factors on the driver's behavioural and psychophysiological parameters could lead to the refinement of driver-vehicle interaction systems and thus alleviate the driver's workload while driving. This is the goal of many academics and industrialists who are improving driver intervention and support systems. Furthermore, the study of the relationship between driver individual characteristics (sex,

driving experience) and driving activity could contribute to the development of human-machine interface strategies in the field of driving.

The work presented here is included in European project NextPerception, which aimed to facilitate the integration of versatile, secure, reliable, and proactive human monitoring solutions in the health, well-being, and automotive domains (Nextperception, 2020). One part of the project focused on the development of systems based on a distributed architecture of sensors and artificial intelligence components that perform complex human monitoring functions, such as the Driver Monitoring System (DMS). To do this, several Italian academic and industrial groups were involved in this project, each to develop a module capable of detecting a driver's behavioural and psycho-physiological characteristic (e.g., Arousal, visual distraction). Each module was integrated into a driving simulator in order to obtain the Driver Monitoring System (DMS) (Figure 1).

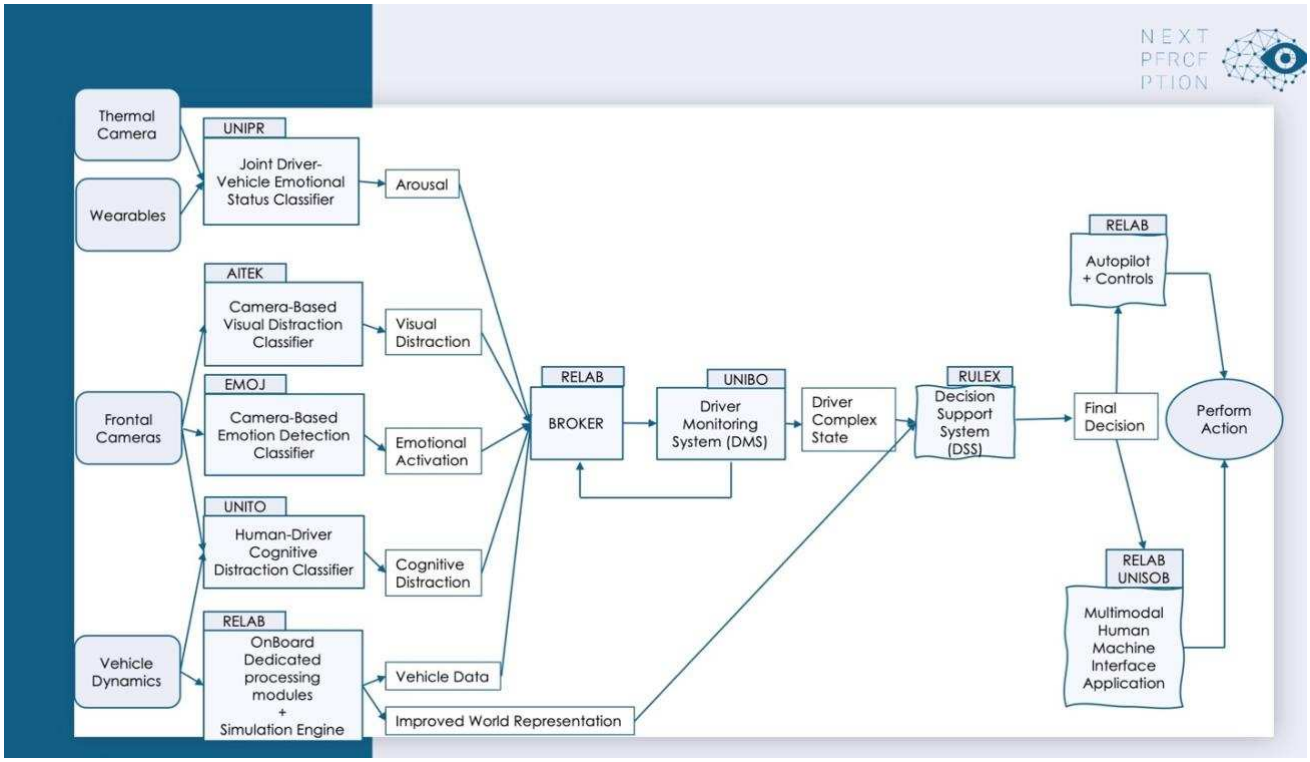

Figure 1. *Flowchart of NextPerception project. The Italian academic and industrial partners involved are represented with their relative contributions to the project. Each partner developed a module (e.g. arousal, visual distraction) and all were integrated to capture the driver's complex state and activate the appropriate solutions (HMIs).*

The NextPerception DMS aims to provide information on the driver's state of health, i.e. to obtain the so-called Driver Complex State (DCS), derived from a series of parameters including cognitive distraction, visual distraction, emotion and driver arousal, thus enabling intervention in dangerous driving situations. Therefore, based on the combination of cognitive, emotional and behavioural data collected, such a DMS would be able to provide data and obtain a fitness to drive index from 0 to 100 that estimates the driver's ability to be in control of the vehicle (Andruccioli et al., 2023). This information on the driver's state, combined with an estimate of the external driving environment, is exploited by a decision support system (DSS) responsible for determining the most appropriate action to support the user. For instance, in scenarios of unfit driving, the proposed solutions ranged from recovery strategies, such as calming or reorienting the driver, to handing over control of the vehicle from the driver to the automation for safety reasons. The strategies were applied via human-machine interfaces (HMIs) and were designed to help the driver in the case of activation states that were too high (e.g. anger, stress) and too low, such as drowsiness (Presta et al., 2023). In this context, our contribution to the NextPerception project included the development of the Joint Driver-Vehicle Emotional Status Classifier (JDVS), a system for detecting the arousal driver state (see Appendix). Therefore, an experimental study was conducted to test and train the various components of the driver monitoring system, and physiological data recorded and collected through a wearable device was used to study the effects of the driver's mental workload resulting from different distraction tasks on physiological parameters during the driving simulation.

3.2 Aims

The main purpose of the present study was to monitor the driver's physiological state during a simulated low-traffic highway driving scenario, in which the participant was subjected to various distraction tasks. In this case, the driving simulator was used because it makes it possible to create driving scenarios by controlling environmental interference that is common in an ecological experiment. In addition, it was possible to manipulate the level of workload with exposure to secondary tasks (e.g. cognitive memory task and mobile phone use) simultaneously performed at the primary driving task in a safe and controlled setting. Cardiac autonomic activity was monitored by assuming variations according to the amount of mental workload derived from distractive stimuli during the primary driving task. We hypothesized an increase in stress response as a function of increased workload due to increasing task complexity (e.g. from a just driving while following a car to a task of visual, cognitive and emotional distraction while driving). Moreover, we aimed at examining the potential sex differences in cardiac autonomic activation while driving in distracted conditions.

3.3 Methods

Participants

Twenty-nine volunteer subjects were recruited in the study, and all signed the informed consent before starting the experiment. Eligibility criteria included being in good health (no history of cardiovascular or mental disorders) and having held a driver's license. A sample size calculation was not deemed necessary because of the exploratory nature of this study. Due to technical problems, data from one participant were excluded in the overall analysis. The final sample consisted of twenty-eight healthy drivers (15 males, 13 females, mean age: 35.25 ± 10.75 (SE=2.03) years, range 24-58 years). All the participants had held a driver's license at least three years.

Experimental design

The experimental procedure was described in a study of Presta and colleagues (Presta et al., 2023) and in the NextPerception final report (Plomp, 2023).

This study was carried out on the RE.LAB driving simulator based in Reggio Emilia, Italy. The experimental procedure included seven different phases (Figure 2) associated to a series of distracting tasks in order to increase level of mental workload. Drivers were recommended to abstain from caffeine and nicotine consumption for at least two hours prior to the driving task as these variables may have transient effects on cardiovascular measurements (Laborde et al., 2017). Upon their arrival to the RE.LAB, each participant received informed consent, was equipped with Equivital EQ02 Life Monitor (Equivital EQ02, Hidalgo, UK), which allows real time acquisition of ECG signals, and various questionnaire were administered (for psychometric results and more details see Presta and al., 2023). After this preliminary procedure, participant was accompanied in the simulator room to perform the experimental tasks. The driving scenario was designed with SCANeR Studio 1.7 platform and consisted of a medium-traffic highway in manual mode. At the beginning,

the participant sat relaxed on the simulator seat to acquire two minutes of baseline recordings. Each subsequent experimental phase lasted two minutes. After the baseline, the subject started to drive following a car and in this phase only performed the driving task (car following phase). Then, a series of dual tasks were completed. While the driver was driving following the same car, he/she simultaneously completed several activities in sequence, including cognitive, emotional and visual distraction solicitation tasks. The order and the structure of the dual tasks was as follows:

- Cognitive distraction (CO): the driver performed three N-back tasks. In the N-back tasks, a series of letters of the alphabet were presented in random order and the driver had to respond 'match' as quickly and accurately as possible when a pronounced letter matched the 2-back letter.
- Cognitive + visual distraction (CO+VIS): the driver listened to a recorded voice saying two city names and had to write down the names of the mentioned cities on his/her smartphone. The couple of city names was updated every 20 seconds five times during the two-minute session.
- Emotion (EM): the driver had to drive while listening to a song. Two songs were chosen to induce additional emotional arousal. The songs used were selected from the Database for Emotion Analysis using Physiological signals (DEAP database) considering their property of eliciting the highest emotional levels (Koelstra et al., 2011). The songs were 'Seven Nation Army' by the White Stripes and 'Beautiful People' by Marilyn Manson and were presented randomly (Presta et al., 2023).
- Cognitive + emotion+ visual distraction (C+E+V): while listening to the music track started in the previous session, participants are asked 3 times to text on their smartphone a phrase about their perceived emotions in that moment. This allowed to test for the induced emotion and to add visual and cognitive distraction to the driving session.

At the end of C+E+V phase, driver was asked to stop the car and sit relaxed in order to acquire recovery recordings. The driving trial, which lasts 14 minutes in total, is guided by a recorded voice that recalls the activities to be performed by the driver in each session.

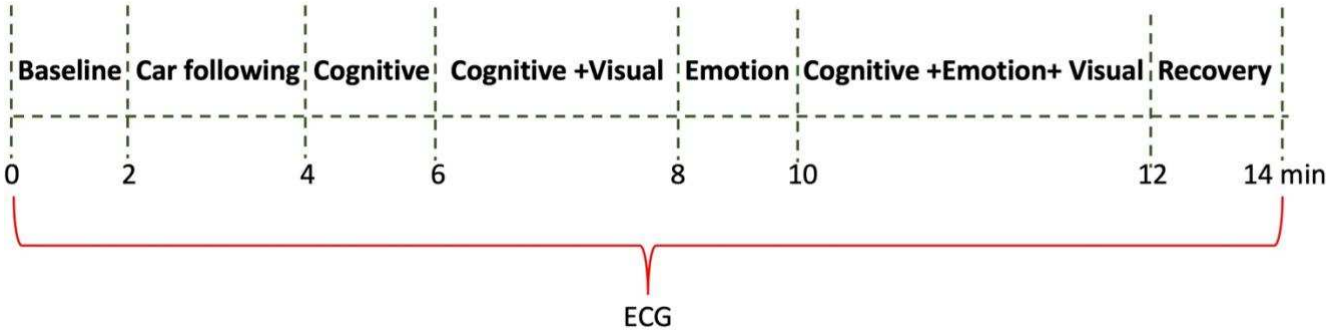

Figure 2*. Timeline of the experimental procedure.*

Heart Rate and Heart Variability Analysis

ECG signals obtained with the EQ02 LifeMonitor equipment were exported using Equivital Manager software and analysed by means of Chart5 software (ADInstruments, Sydney, Australia). Initially, each raw ECG signal was manually inspected to ensure that all R- waves were correctly detected and to exclude artefacts before further analysis. For each recording period, ECGs were split in 2-min epochs. For each epoch, HR (beats per minute) and HRV indexes were generated. It has been used the root mean square of successive beat-to-beat interval differences (RMSSD, ms) as a vagally-mediated index of HRV. Average HR and HRV values were calculated for each 2-min epoch.

Statistical Analysis

Data are expressed as means ± standard error (SE). Statistical analyses were performed with the software package SPSS (version 28) (SPSS Inc., Chicago, IL). Statistical significance was set at $p < 0.05$. The normal distribution of variables was determined using the Kolmogorov-Smirnov test.

Differences in sex were analysed as potential explanatory component of psychophysiological modulation during driving.

Considering the full sample, cardiac autonomic responses to the driving task were analysed with a one-way ANOVA for repeated measures.

Differences between the sex group (male vs female) in age were analysed by Student's t-tests. Cardiac autonomic responses to the simulated driving task were analysed with a series two- way ANOVAs for repeated measures, with “group” (male vs female) as the between subject factor and “recording period” as the within-subject factor.

3.4 Results

Cardiac autonomic responses to the simulated distracted driving task

Figure 3 shows cardiac autonomic response to the simulated distracted driving task for the full sample of drivers. A one-way ANOVA for repeated measure yielded a significant effect of "recording period" for HR (F=20.20, $p < .001$, $\eta_p^2 = .428$) and RMSSD (F=12.54, $p < .001$, $\eta_p^2 = .317$). Considering the full sample, HR was significantly higher during CF (82.66 $\pm$ 1.89 bpm, $p < .001$), CO (84.55 $\pm$ 2.10 bpm, $p < .001$), CO+ VIS (82.34 $\pm$ 1.89 bpm, $p < .001$), EM (80.53 $\pm$ 1.79 bpm, $p < .012$) and C+E+V (80.01 $\pm$ 1.79 bpm, $p < .011$) compared with baseline value (76.16 $\pm$ 1.90 bpm) (Figure 3A). RMSSD values were significantly lower during CF (24.06 $\pm$ 2. 15 ms, $p < .001$), CO (21.06 $\pm$ 2.12 ms, $p < .001$), CO+ VIS (23.04 $\pm$ 2.44 ms, $p < .001$), EM (24.22 $\pm$ 2.54 ms, $p < .001$) and C+E+V (23.88 $\pm$ 2.32 ms, $p < .001$) compared with baseline value (32.76 $\pm$ 3.04 ms) (Figure 3B).

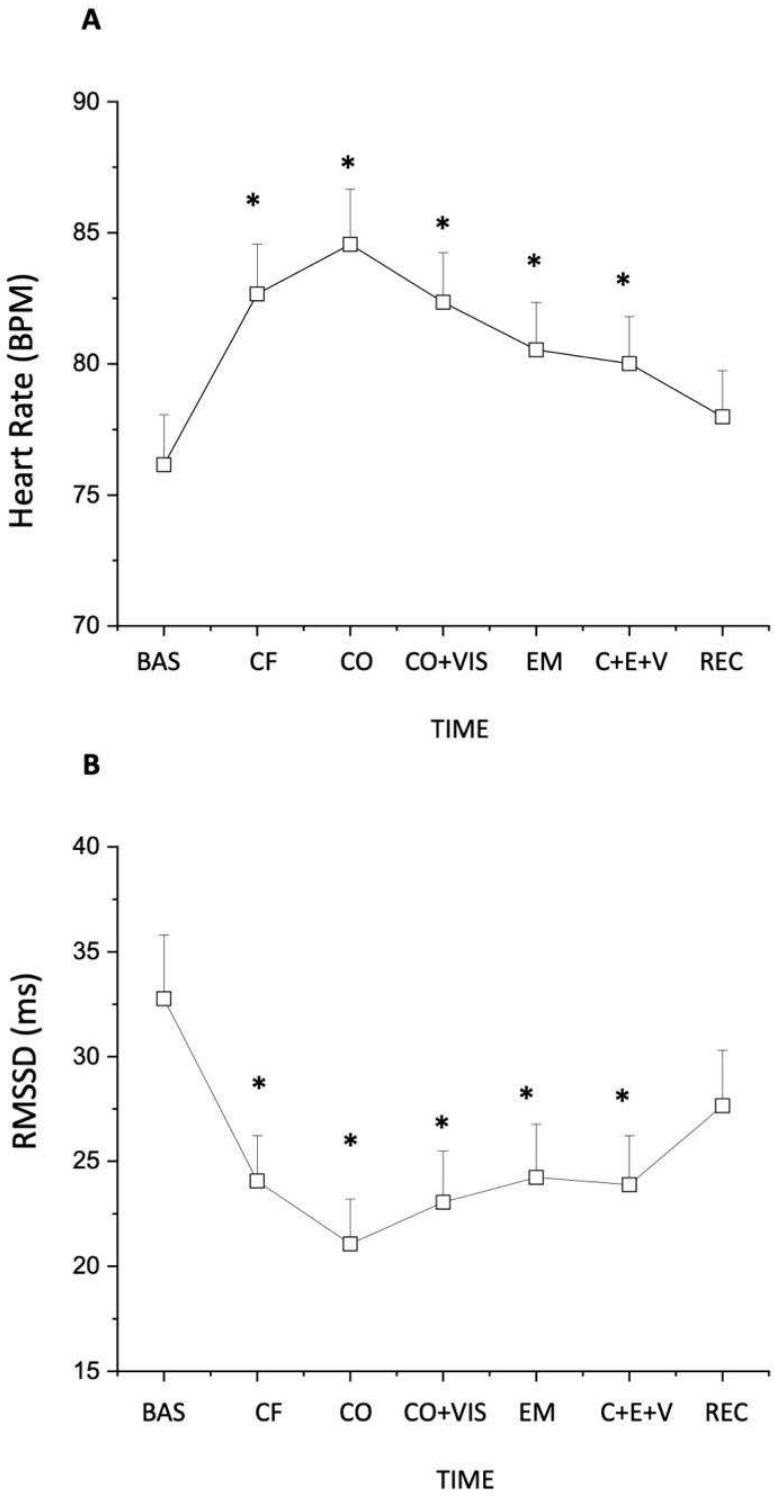

***Figure 3**. Heart rate (A), heart rate variability (B) responses to the simulated driving task for the full sample of drivers (n = 28). Data are reported as mean ± standard error. Abbreviations: BAS = baseline; CF = car following; CO = Cognitive distraction; CO+VIS = Cognitive+ Visual distraction; EM= Emotion; C+E+V= Cognitive + Emotion + Visual distraction; Rec= recovery; RMSSD = root mean square of successive beat-to-beat interval differences. (p < .05: * = vs BAS)*

Exploring sex differences in cardiac autonomic responses to the simulated distracted driving task

There were 15 male and 13 female drivers. There were no significant age differences between women and men. Their mean±SE age was respectively 34.86 ± 2.83 years and 35.69 ± 3.03years (t=-.199, p=.844).

Figure 4 shows cardiac autonomic response to the simulated distracted driving task in males and females. Two-way ANOVAs for repeated measured yielded a significant effect of "recording period" for HR ($F = 19.58$, $p < .001$, $\eta_p^2 = .430$) and RMSSD ($F = 12.19$, $p < .001$, $\eta_p^2 = .317$) during the simulated driving test. However, these effects were independent from drivers' sex.

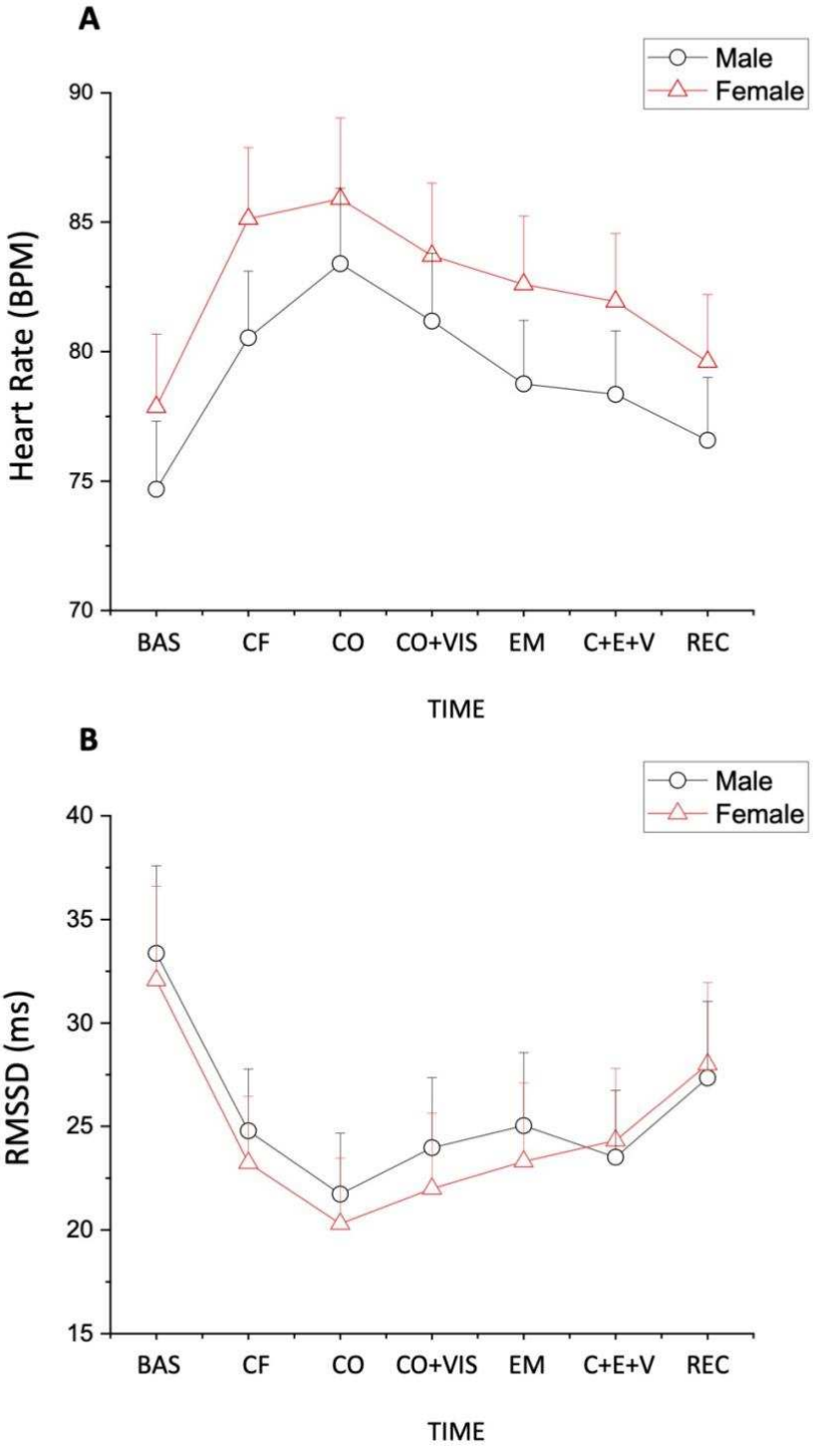

Figure 4. *Heart rate (A), heart rate variability (B) responses to the simulated driving task in male (n= 14) and female (n=14) drivers. Data are reported as mean ± standard error. Abbreviations: BAS = baseline; CF = car following; CO = Cognitive distraction; CO+VIS = Cognitive+ Visual distraction; EM= Emotion; C+E+V= Cognitive + Emotion + Visual distraction; Rec= recovery; RMSSD = root mean square of successive beat-to-beat interval differences.*

3.5 Discussion

Distracted driving can be recognized as a serious safety risk factor for drivers and other road users. Among distractive factors, the use of or manipulation of technological devices while driving can reduce the amount of attentional resources needed for road vigilance and vehicle control (Svenson et al., 2005). Several studies have analysed the relationship between driving performance and distraction situations due to the manipulation of mobile phone, i.e., writing and reading text messages. Research has focused on driver response to risky traffic events (e.g. potential pedestrian collisions) and the impact of distraction on driving performance by analysing a number of measures of eye movement and driving performance (Amini et al., 2023). Results have highlighted a deterioration of vehicle control, i.e., a higher deviation of car lateral positioning was noted during distracted driving. Strayer et al. (2006) found that talking on the phone (even with hands-free systems) impaired visual perception and reactions to traffic changes, resulting in impaired driving performance. Therefore, being engaged in a secondary activity while driving can impair the ability to remain alert at the wheel. The development of intelligent systems that can recognize the overall state of the driver and intervene in case of emergency or dangerous situations (e.g., distraction, drowsiness) is the goal of many industrialists and researchers in the automotive domain. The NextPerception project aimed to develop a system based on a distributed architecture of sensors and artificial intelligence components capable of detecting the driver's state and initiating recovery or support strategies based on the driver's ability to remain behind the wheel. In this context, an experimental protocol was designed to test and train the different components of driving monitoring system integrated in a driving simulator. Cognitive, emotional and visual distraction conditions while driving were included in the protocol to assess how driver’s state varied as a function of distraction tasks of increasing complexity. In this thesis, only physiological data collected to assess the effects of the driver's mental workload, manipulated by distractive tasks, on

neurovegetative parameters were considered. In order to acquire information about driver's physiological response in distractive conditions, we investigated cardiac autonomic modulation during a simulated driving scenario by means of a HRV measurements. Environmental factors such as road conditions, weather and traffic flow have been shown to have an impact on the performance and mental state of the driver (Dwight and David, 1997; Hill and Boyle 2007, Healey and Picard, 2005; Westerink et al. 2008). In this study, participants were exposed to a low-traffic highway driving scenario to limit the effects of these environmental factors. In order to study the effects of distraction on the driver, the participants were exposed to various dual-task conditions, i.e. driving and performing tasks that induced different types of distraction from the primary driving task. For instance, they were asked to divide their attentional resources between driving and cognitive tasks, such as performing memory exercises of N-back task while simultaneously paying attention to the road and the car they were following. In fact, several studies have shown an increased stress response during dual-tasking, even in a driving context (Heine et al., 2017; Mehler et al., 2012).

Considering the full sample of our research, HR significantly increased and HRV (RMSSD) significantly decreased compared to baseline conditions, with such effects persisting throughout the simulated driving task. Specifically, we observed a sharp change in HRV once participants began driving following the car and this finding is in line with our previous research in real road driving context (see chapter 2). Furthermore, the driver's workload was expected to increase further due to the simultaneous addition of visual distraction during the tasks, i.e. the use of the telephone while performing the cognitive, emotional and driving task, and this was thought to result in increased physiological activation of the driver. Indeed, several studies have shown that mobile phone use can impair driving ability and affect a driver's psychophysiological response, observable in a reduction of the HRV (Collet et al., 2009; Kass et al., 2007). However, no differences in cardiac autonomic response were found between different tasks with different attentional and distractive engagement

(e.g. car following vs. cognitive + visual distraction or vs cognitive+ emotional + visual distraction period). These results could be explained by the experimental procedure and the type of tasks included in the protocol. It is possible that the exposure of the participants to different types of tasks, for too short limited time, did not result in a strong and clear physiological response to driving distraction. In addition, the simulated driving environment may have contributed to limiting the real effects of distracted driving, as it may be perceived as less immersive and truthful.

Furthermore, sex has been considered as a modulating factor in driving behaviour (Montgomery et al., 2014; Cordellieri et al., 2016), but few studies have investigated psychophysiological differences. We examined this variable as potential modulatory components for cardiac autonomic responses during driving, even in simulated distracted driving situations. No differences in autonomic response emerged when males and females were compared. This result is in line with our previous research in a real-world driving context, in which no significant difference in cardiac autonomic modulation was found with respect to the sex of the driver. However, one study showed a sex difference in distracted driving behaviour. Participants were exposed to driving simulations in high and low traffic conditions while performing a secondary task on a mobile phone, and the physiological response was monitored by HRV analysis and driving behaviour was assessed. The results indicated that women exhibited, on average, reduced heart rate variability and more dangerous driving behaviour (e.g., significantly higher average acceleration and speed) than male drivers (Arca et al., 2022). Our results of the simulated driving experiment are not in line with this study and could probably be explained by the fact that our participants performed the driving simulation in low-traffic conditions, with no external environmental effects that could increase the stress perceived by the driver. However, even our real road study with different environmental solicitations (urban road vs. ring-road) did not produce the expected results. As anticipated, driving is a very complex activity and individual factors lead to great variability in driving behaviour.

Overall, the results of the study revealed significant overall autonomic activation while driving, even in a simulated driving environment, regardless of exposure to the amount and different conditions of distraction and sex.

3.6 Conclusions

The design and implementation of in vehicle-artificial intelligence models capable of monitoring and recognising the driver's state is the goal of the near future to reduce road accidents. One of the most dangerous factors when driving is distraction. This unsafe situation can be caused by several factors, such as the manipulation of technological devices, which can compromise the attentional resources needed to supervise the road and control the vehicle. The NextPerception project aimed to develop an initial system to monitor the driver and investigate support strategies via human-machine interface. In order to collect information and to train the components of DMS, an experimental study was conducted in a simulated driving environment. In this context, physiological data from a wearable device were used to study the effects of mental workload on the cardiac autonomic response of a car driver. Thus, the main purpose of the present study was to monitor the driver's physiological state during a simulated low-traffic highway driving scenario, in which the participant was subjected to various distraction tasks. HRV analysis revealed significant overall autonomic activation during driving, independent of exposure to additional secondary distractive tasks and sex. This result could be explained by the nature of the driving activity, which itself requires cognitive, attentional and physical resources, even in simulated driving environment. As already extensively described, the experimental protocol included a number of distractive secondary tasks while driving, which were presented sequentially by changing the content and nature of the task, e.g. the n-back task and then writing on the phone the names of the cities heard by the voice guide. On the one hand, the reason was to increase the driver's difficulty in paying

attention to the primary driving task (e.g., driving and answering questions verbally vs. driving, paying attention to task instructions and answering questions with the mobile phone). On the other hand, it was due to collect data and train the different components/algorithms of the DSM NextPerception (e.g., through the visual distraction task train the visual distraction algorithm to obtain the information). Probably the sequence of different tasks for too short a time influenced the impact of the distracting contents, or more precisely did not lead to a clear and strong distraction response while driving on the cardiac autonomic response. In summary, our results suggest that the overall driving task produced a notable impact on cardiac autonomic neural modulation, even in simulated driving environment. Study limitations included collecting data from a small sample size, thereby limiting our ability to find associations between individual characteristics and cardiac autonomic responses. Further investigations with larger sample sizes could reveal an association between sex and cardiac autonomic activation during driving, which did not emerge in this pilot study.

In the future, it would be useful to investigate the driver's physiological state in relation to his/her driving behaviour during the task, by retrieving data from the driving simulator (e.g. vehicle speed variation, hard braking events, steering entropy, following distance, lane deviation) and correlating them with cardiac autonomic activation and psychometric characteristics. Lastly, it could be interesting to evaluate the impact of HMI strategies on driver’s psychophysiological response, especially in dangerous or problematic situations, such as poor sleep quality, fatigue or generally in altered arousal state.

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CHAPTER 4. – Study 3: Physiological monitoring of driver fatigue in simulated autonomous and manual driving environments

4.1 Introduction

Fatigue is a multidimensional concept that involves physical and mental fatigue, and can result from a variety of causes, such as an overload of an individual's cognitive resources, or occur as a result of a sleep deficiency (May and Baldwin 2009). It includes symptoms as difficulty in maintaining attention, concentration, focus, vigilance and staying awake (Soares et al., 2019). In the driving context, fatigue is considered to be the main cause in road traffic accidents, as it makes the driver more vulnerable to the road environment, which is always unpredictable and requires optimal attentional resources in order to perform the driving task safely. In fact, being in a psycho-physiological state of under-arousal such as fatigue leads to altered reaction times, reduced vigilance, information processing deficits and decreased attention, all of which are extremely dangerous while driving a vehicle (Zeng et al., 2024). Moreover, several external factors could induce and increase the perception of driver fatigue. It has been observed that driving time could be an explanatory factor for driver fatigue (Di Stasi et al., 2015). In fact, monotonous and simultaneously prolonged driving can impair alertness required for safe driving (Aidman et al., 2015). Moreover, time of the day is considered an important risk factor in road accidents. Fatigue-related accidents are most frequently observed between 2 a.m. and 6 a.m. and again between 2 p.m. and 4 p.m (Williamson &Friswell, 2011). Due to the high number of road accidents caused by fatigue, interest has grown in recent years to better understand the phenomenon and in particular to explore its psychophysiological aspects during driving. Among several physiological methods to assess cognitive and health states, heart rate variability (HRV) and thermal infrared imaging (TII) are widely used as peripheral and non-invasive physiological measurement tools in various clinical and research fields. HRV is an indirect, non-invasive measurement of beat-to-beat temporal changes in

heart rate, which reflect the dynamic changes of cardiac autonomic modulation at the sinoatrial node of the heart, but more specifically is able to index cardiac vagal tone (Shaffer et al., 2014; Thayer et al., 2009). TII is a non-invasive instrument for assessing body temperature, monitoring human arousal and estimating breathing rate. In particular, it is possible to track changes in skin temperature in different regions of interest (e.g., nasal tip, forehead), whose variations may reflect emotional and mental conditions (Ioannou et al., 2014, Hassoumi et al., 2022). Thus, both methods are able to reveal the psycho-physiological state, as they reflect the activity of the autonomic nervous system in response to emotional stimuli and mental conditions, and can provide an insight into the driver's mental state and workload. In driving research, fatigue is investigated by manipulating driving time and driving scenario. The most common technique for inducing driver fatigue is the exposure to a monotonous driving scenario with the aim of driving for more than three hours (Li et al., 2009; Kee et al., 2010; Fu et al., 2016). Several studies have investigated the relationship between driver fatigue and the driver's behavioural and physiological response using HRV and TII. For instance, a simulated driving study monitored physiological parameters after 2-hours driving. Compared to the beginning of the driving task, heart rate and LF/HF decreased, as well increased fatigue symptoms after driving (Liang et al., 2009). Schmidt and colleagues (2009) studied the effects of monotonous daytime driving on vigilance state in a real-world driving context. The participants performed a driving task of approximately four hours on a low-traffic motorway outside rush hour. The authors observed a continuous reduction in vigilance indicated by all performance and physiological measures. In particular, the results showed a linear decrease in heart rate until the end of the task. Another study assessed mental fatigue in a sample of professional bus drivers through HRV indices. Compared to the start of the task, a decrease in HR was observed after 3 hours of driving and this effect was maintained until the end of the experiment, after 6 hours total driving time (Lecca et al., 2022). In addition, infrared thermography was used in a simulated driving

study to monitor changes in nasal tip temperature under fatigue conditions during a 2-hour driving session. It was observed that the nasal skin temperature changed as a function of driving time, i.e. it increased for the first 75 minutes of driving, then began to decrease, but this decrease gradually normalized as time passed (Diaz-Piedra et al., 2019). Therefore, the use of physiological signals such as HRV and TII can be useful in monitoring the driver's physiological state under fatigue conditions while driving. Considering that driver fatigue and its associated consequences represent a significant safety risk for drivers and road users, various strategies to mitigate these risks are being developed and evaluated. For instance, recent advancements in technology have facilitated the emergence of various driver assistance systems, leading to the development of autonomous driving. Autonomous driving can be defined as an innovative approach to vehicle design that integrates advanced technologies such as artificial intelligence and sensor systems to reduce human involvement in driving. The levels of driving automation are classified into six numerical categories, ranging from full manual control (Level 0) to full automation (Level 5), as established by the Society of Automotive Engineers (SAE). Levels 3 to 5 refer to highly automated vehicles that do not require driver intervention in most (Levels 3 and 4) or all circumstances (Level 5). In contrast, lower SAE levels (0 to 2) still require human intervention (SAE, 2019). Thus, by minimizing driver engagement, autonomous systems have the potential to reduce human driving errors, enhance safety, and alleviate the driver's workload. As a result, research interest is being directed toward evaluating the impact of autonomous driving on driver capabilities, particularly as vehicles classified as Level 3 and above are projected to become the dominant mode of transportation in the future. However, knowledge regarding the effects of autonomous driving on driving behavior remains limited, especially in high-risk contexts such as stress or fatigue. Given its potential to mitigate the negative effects of unsafe driving, it is crucial to conduct investigations using physiological methods approach to gain a deeper understanding of the potential effects of autonomous driving on the driver fatigue.

4.2 Aims

On the basis of the premises above, the present study aimed to monitor the driver's physiological state during a prolonged and monotonous simulated driving task, designed specifically to induce and investigate driver fatigue. We expected a clear effect due to the time-on-driving, that is an effect on the fatigue level of the participants due to the (long) duration of the task. Furthermore, in order to explore the potential modulatory effects of autonomous driving on fatigue, autonomous and manual modes were included in the simulated driving scenario. Therefore, we hypothesised that the effect of fatigue could be modulated by the driving mode (autonomous or manual driving). Cardiac autonomic activity and skin temperature were recorded and monitored by wearable and remote sensors, assuming variations based on the amount of driving time and driving mode.

4.3 Methods

Participants

Twenty professional drivers (19 men) participated in a 3-h simulated driving session in the early morning. The mean age and body mass index (BMI) (standard deviation [SD]) were 44.8 (SD = 7.3) years old, and 26.08 (SD = 3.6) kg/m^2, respectively. All the drivers were right-handed, and all had normal or corrected-to-normal vision. Before the driving session, participants were required to abstain from alcohol for 24 hours and caffeine-based beverages for 12 hours. On average, they slept 7.03 (SD = 0.57) hours the night before the experiment. All participants began the experimental session with proper levels of arousal (Stanford Sleepiness Scale score not greater than 3; Hoddes et al., 1973), indicating no fatigue or sleepiness (Diaz-Piedra et al., 2019). All participants gave written informed consent before taking part in our study, and received monetary compensation for their time.

Experiment Design

We conducted a study using a 2x2 within-subjects experiment with driving time (3-h) and driving modality (2 levels: manual [MD] vs. automated [AD] driving). After 90 minutes of driving, a fixed-time (i.e., 15 seconds) take-over signal was given to transition between automated [AD] and manual driving [MD] or vice versa. The starting driving mode (whether participants start in MD or AD condition) was counterbalanced among the participants. Throughout the driving simulation, we collected physiological data (skin temperature and cardiac activity) to monitor drivers' states.

Experiment procedure

The study was run in agreement with the Code of Ethics of the World Medical Association (WMA, 2013) and under the guidelines of the University of Granada´s Institutional Review Board (IRB approval 1528/CEIH/2020). The experiment was conducted at the Neuroergonomics and Operator Performance Lab of the University of Granada (Granada, Spain). The laboratory has two windowless rooms: the driving simulator room and the control room. Both rooms have a climate control system to maintain stable temperature and humidity levels. Participants were also provided with a short-sleeve cotton T-shirt to wear while driving to ensure consistent upper-body clothing for each participant. After a 5-min driving training session, the ECG wearable sensor was placed on participant skin. Afterwards, participants were asked to rest while looking at a red fixation point displayed in the middle of the simulator's central screen for 5 minutes (physiological baseline). This was followed by a control scenario for 5 minutes (2.5 minutes in manual driving mode and 2.5 minutes in autonomous driving mode) to familiarize the participants with the experimental setting. Another physiological baseline was recorded after the control scenario. The driving scenario lasted for 3 hours (1.5 hours in MD and 1.5 hours in AD). After 1.5 hours, a driving modality shift was performed. In manual driving mode, participants drove following usual traffic rules with a speed limit of 130 km/h, maintaining the car in the right lane and keeping their hands in the 10-10 position. In autonomous driving mode, the task was to supervise the simulation system. Figure 1 shows the timeline of experimental procedure.

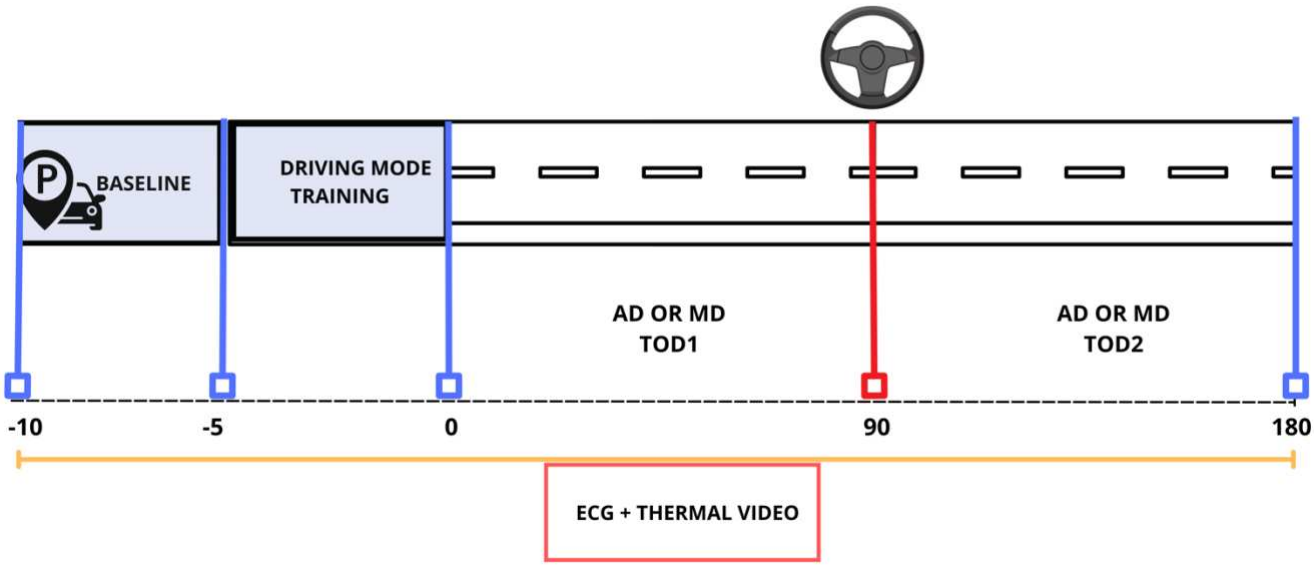

***Figure 1**. A scheme of the experimental timeline. Participants took part in one driving simulation session that lasted ~3 h. **Driving simulation**: 1.5 h in MD or AD (TOD1); shift in driving modality at 90 min (from MD to AD or viceversa); 1.5 h in MD or AD (TOD2).*

ECG recording and analyses

We used a BiosignalsPlux Research Kit (PLUX Wireless Biosignals, Lisbon, Portugal) to monitor participants' ECG data. The BiosignalsPlux system includes a wearable hub with an 8-channel configuration (analog ports) of 16-bit per channel resolution, using Bluetooth data transmission technology. A set of disposable, self-adhesive, pre-gelled Ag/AgCl electrodes (24 mm diameter) was employed for ECG measurement. The ECG was recorded with a single-lead local differential bipolar sensor (0.5-100 Hz bandwidth, ± 1.47 mV range), including a positive, a negative, and a reference cable, each one ending with a dedicated electrode socket. Once we cleaned the skin, we placed the electrodes on the participant's chest (Lead II configuration): one electrode on the depression below each of the shoulder blades (reference on the left side, positive on the right side) and one electrode (negative) on the fifth intercostal space of the left side. All the raw data were pre-processed to ensure the correct sampling rate and divided into 5-min blocks.

Thermographic recordings and analyses

To collect the driver's facial and upper-body skin temperature, we used a high-resolution science-grade LWIR camera (A325sc – FLIR; Teledyne FLIR LLC, Wilsonville, Oregon, USA). The camera (resolution of 640 × 480 pixels) was placed on a support ~140 cm above the moving platform and ~140 cm from the driver's face (angled from above ~26°). Automatic focus was always employed for the video recording. The signal was continuously recorded at 30 Hz. The main relevant POI was nasal tip. Regarding nasal tip, research indicates that nasal tip is a reliable measure as a stress indicator: when a person experiences stress, this area consistently shows a notable decrease in temperature (Cho et al., 2019; Diaz-Piedra et al., 2019). Initially, two trained and independent researchers (i.e., raters) manually performed data collection and segmentation of the temperature for each POI and participant through a customized MATLAB graphical user interface. Data were collected each minute, thus identifying 180 1-min bins. After calculating the initial degree of agreement between the raters (ICC, see the "Statistical analysis" section), we identified the discrepancies in their observations. We considered a measurement disagreement when (i) the difference in the recorded temperature exceeded 0.5 degrees and (ii) there was a discrepancy in measurement availability (e.g., coder 1 reported the measure in a specific frame as not available while coder 2 reported it and vice versa). For this reason, a third trained, independent rater reviewed the videos to solve the disagreements. The third judge had a decision-making role, and therefore his/her assessment is considered conclusive in cases of disagreement. Finally, we calculated again the ICC after the disagreement resolution.

Driving simulation and performance

Participants drove a semi-dynamic (a four-degree-of-freedom motion platform) driving simulator (Nervtech™, Ljubljana, Slovenia) recreating a middle-sized electric automatic vehicle. To control the

vehicle, participants used a Skoda Octavia steering wheel (Škoda Auto a.s, Mladá Boleslav, Czech Republic), and gas and brake pedals (Sensodrive GmbH, Weßling, Germany) while seated on a Ford-Max seat installed on a rotating base turning swivel platform (Ford Motor Company, Dearborn, Míchigan, US). Speedometer and analog tachometer gauges are displayed on a dedicated screen placed behind the steering wheel. A Logitech 5.1 audio surround system (Logitech International S.A., Lausanne, Switzerland) reproduces engine sound, traffic noise, and vocal warnings (e.g., the driving modality shift requests). Participants were seated, without breaks, for about 3-h, either driving or supervising the automation (depending on the driving modality) around the same road scenario without traffic. The driving scenario consisted of a six-lane monotonous highway circuit developed using SCANeR studio software (AVSimulation, Boulogne-143 Billancourt, France; version DT 2.5). The road was ~ 33.5 km long with a 3.5 m wide median, and it was surrounded by an empty and monotonous grassy meadow. The driving scenario was displayed via three 49" screens with a resolution of 3840 x 2160 pixels, which were set into a panoramic arrangement to simulate the horizon of the virtual world (~130° field of view). The drivers sat about 135 cm away from the main central screen.

Statistical Analysis

In order to perform the statistical analysis, we categorized the 3-h of the driving task into 90 2-min bins for Nasal skin temperature and into 36 5-min bins for Heart Rate. For the analysis of the nasal skin temperature, we calculated intraclass correlation coefficient (ICC) estimates to detect the agreement between the researchers (i.e., raters) about the skin temperature of nasal tip. ICC estimates and their 95% confident intervals were computed, based on a mean-rating (k = 2), using a 2-way mixed effects model for absolute agreement between raters. To analyse changes over time (3-hour driving session, 90 time points for nasal tip, 36 time points for heart rate) and driving

modality order (i.e., AD – MD [order 1], MD – AD [order 2]) in nasal skin temperature (nasal tip) and heart rate, linear mixed models were applied. Specifically, we examined various individual growth curve models using maximum likelihood estimation to analyze intraindividual variations in the patterns of change of the dependent variables (Singer and Willett, 2003). Firstly, we fitted the unconditional means models to examine variation in dependent variables without regard to time. To achieve this, we conducted one-way ANOVA models with participants as a random effect, excluding any predictors. Next, we fitted unconditional linear growth models to assess variance across individuals and linear time. We then explored non-linear (quadratic and cubic) individual growth trajectories over time. For both linear and curvilinear growth patterns, we estimated the average initial status and trajectories within individuals over time, treating time (in bins) as both fixed and random effects. To explore the effect of the order between autonomous and manual driving, we fit another model by adding the driving modality order factor to the best fitting model (a lower Akaike's Information Criterion [AIC] value indicates a better fit). For both variables, the cubic growth model was the best fitting one. For each model, we present parameter estimates and standard errors (SE). Significance levels were set at $\alpha < 0.05$.

4.4 Results

Nasal skin temperature

Considering the original measurements of the raters, the ICC estimate for the tip of the nose was 0.994 [95% C.I. 0.992–0.995]. After the intervention of the third rater (see *Thermography recordings and analyses section*), the ICC estimate for the tip of the nose was 0.998 [95% C.I. 0.997–0.998]. For the successive analyses, we used the mean value of the two raters. To study trajectory changes over time in the tip of the nose temperature, we first tested the linear growth curve model (Model 2). The mean of nasal tip temperature was 33.08 °C and decreased with time ($p < 0.05$). To test the quadratic rate of change (Model 3), we added a quadratic parameter to the previous model. The significant linear effect for the tip of the nose temperature was negative (β = -0.01, SE = 0.01, $p < 0.05$), pointing out a linear decrement over time. The quadratic effect was not significant ($p > 0.05$). To test any cubic changes in individual trajectories over time (Model 4), we added a cubic parameter in the previous model. All three linear, quadratic, and the cubic parameters made a significant contribution to the model (*p-values* < 0.001). The positive effect of linear growth (β = 0.04, SE = 0.01, $p < 0.001$) suggested that the tip of the nose temperature increased at the beginning. The negative effect of quadratic growth (β = −0.003, SE = 0.0004, $p < 0.001$) indicated a deceleration in the increasing linear growth. However, the positive effect of cubic growth (β = 0.00005, SE = 0.0000009, $p < 0.001$) revealed that such deceleration gradually diminished over time. To explore the effect of the driving modality order (Model 5), we added to the best fitting model (Model 4) the driving modality order variable. The linear, quadratic and cubic growth were the same as Model 4 (*p-values* < 0.001). The driving modality order was not significant. However, all the interactions between the rate of changes (linear, quadratic, and cubic) and the driving modality order were significant (*p-values* < 0.001). Table 1 presents the results of the fitting the unconditional means model and the growth curve models. Figure 2 shows the nasal skin temperature (i.e. nasal tip temperature) trend

over the 3-h driving session in both groups.

Table 1. *Results of fitting growth curve models for the trajectory of the nasal skin temperature (tip of the nose) over a 3-h simulated driving session (n=20). It presents parameter estimates and, in brackets, standard errors.*

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Fixed effects					
Intercept	33.08 (0.52) **	33.65 (0.55) **	33.666 (0.55) **	33.26 (0.56) **	33.26 (0.56) **
Rate of change					
Linear	-	- 0.01 (0.01) *	- 0.01 (0.01) *	0.04 (0.01) **	0.04 (0.01) **
Quadratic	-	-	6e-6 (2e-5)	-1e-3 (1e-4) **	-1e-3 (1e-4) **
Cubic	-	-	-	1e-5 (9e-7)**	1e-5 (9e-7)**
Driving modality order	-	-	-	-	-0.25 (0.56)
Rate of change * Driving modality order					
*Linear * Driving modality order*	-	-	-	-	0.03 (0.01) **
*Quadratic * Driving modality order*	-	-	-	-	-1e-3 (1e-3) **
*Cubic * Driving modality order*	-	-	-	-	1e-5 (9e-7) **
Variance Components					
Level 1					
Within-subjects	0.78 (0.03) **	0.33 (0.01) **	0.33 (0.01) **	0.31 (0.01) **	0.28 (0.01) **
Level 2					
In initial status	5.42 (1.72) *	6.17 (1.95) *	6.17 (1.95) *	6.17 (1.95) *	6.17 (1.95) *
In rate of change	-	-0.02 (0.01)	- 0.02 (0.01) *	-0.02 (0.01)	-0.19 (0.01)
Covariance	-	5e-4 (1e-4) *	5e-4 (1e-4) *	5e-4 (1e-4) *	4e-4 (1e-4) *
AIC	4797.68	3374.42	3376.347	3264.03	3109.482

Note. Model 1=Unconditional means model; Model 2=Linear growth model; Model 3=Quadratic growth model; Model 4=Cubic growth model; Model 5 = Cubic growth model with Driving modality order; AIC=Akaike's Information Criterion.

$*p < 0.05$.
$**p < 0.001$.

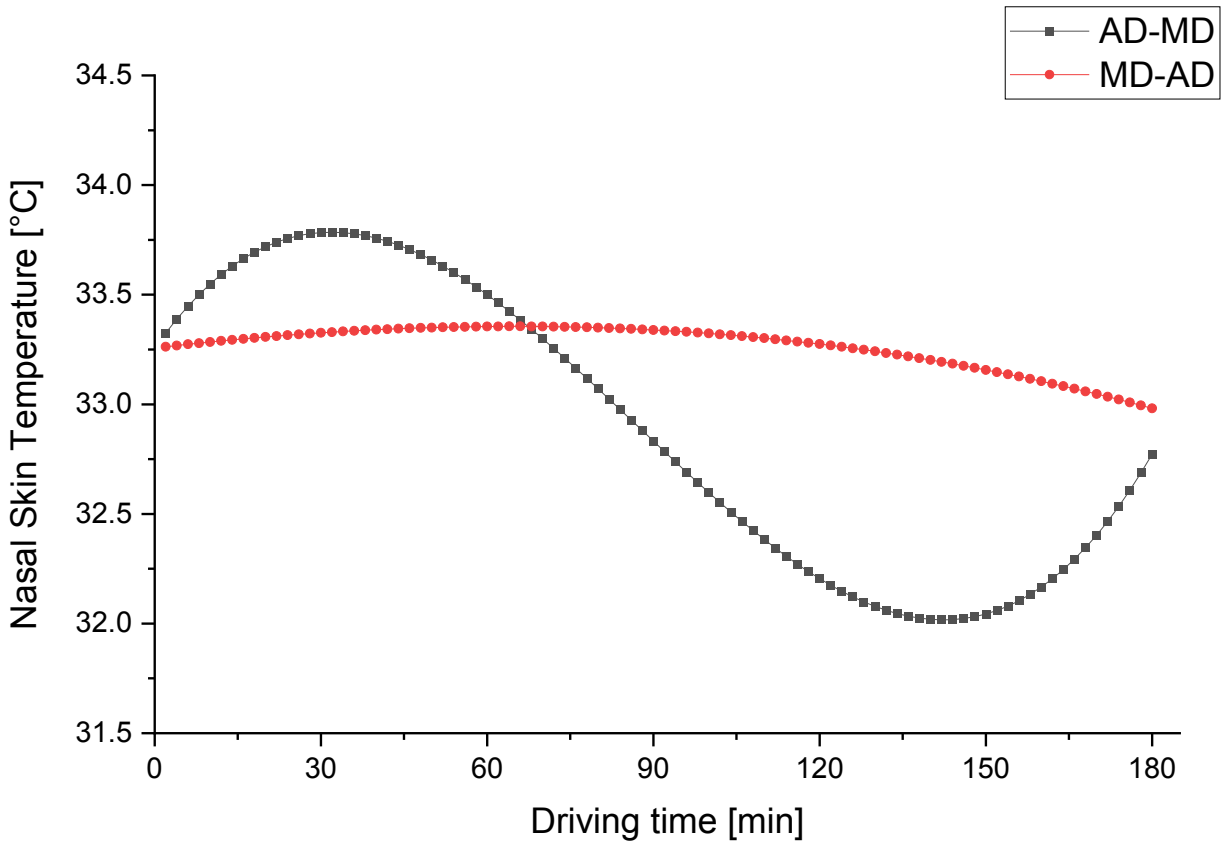

Figure 2. *Effects of driving time (time on task) on the nasal skin temperature. The dotted red curve represents the trajectory of the nasal skin temperature over the 3-h driving session in MD-AD group. The black curve represents the trajectory of the nasal skin temperature in AD-MD. The 90-minute time point represents the moment of the change of driving mode.*

Heart rate

To investigate the trajectory over time in the hearth rate (HR) of the participants, we first tested the linear growth curve model (Model 2). The mean of HR was 63.49 and significantly decreased with time (β = -0.06, SE = 0.02, $p < 0.05$). To test the quadratic rate of change (Model 3), we added the quadratic parameter to the previous model. The linear effect was significant and negative (β = -0.23, SE = 0.03, $p < 0.001$), showing a linear decrement over time. The quadratic effect was significant and positive (β = 0.004, SE = 0.0006, $p < 0.001$), showing an increasing effect after about 60 min. To test any cubic changes in individual trajectories over time (Model 4), we added a cubic parameter in the previous model. Only the cubic parameter made a significant contribution to the model ($p < 0.05$). The positive effect of cubic growth (β = 0.00005, SE = 0.0000009, $p < 0.001$) revealed a gradual acceleration of the increase over time. To explore the effect of the driving modality order (Model 5), we added to the best fitting model (Model 4) the driving modality order variable. The linear, quadratic and cubic growth were the same as Model 4. The driving modality order was not significant. However, all the interactions between the rate of changes (linear, quadratic, and cubic) and the driving modality order were significant (*p-values* < 0.001 for linear and quadratic parameters, $p < 0.05$ for the cubic parameter). Table 2 presents the results of the fitting the unconditional means model and the growth curve models. Figure 3 shows the heart rate trend over the the 3-h driving session in both groups.

Table 2. *Results of fitting growth curve models for the trajectory of the heath rate over a 3-h simulated driving session (n=20). It presents parameter estimates and, in brackets, standard errors.*

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Fixed effects					
Intercept	62.33 (2.19) **	63.49 (2.46) **	64.54 (2.46) **	64.08 (2.47) **	64.08 (2.41) **
Rate of change					
Linear	-	- 0.06 (0.02) *	- 0.23(0.03) **	-0.09 (0.07)	-0.09 (0.07)
Quadratic	-	-	4e-3 (6e-4) **	-4e-3 (3e-3)	-4e-3 (3e-3)
Cubic	-	-	-	1e-4 (7e-5)*	1e-4 (7e-5)*
Driving modality order	-	-	-	-	-0.88 (2.41)
Rate of change * Driving modality order					
*Linear * Driving modality order*	-	-	-	-	-0.28 (0.06) **
*Quadratic * Driving modality order*	-	-	-	-	0.01 (1e-3) **
*Cubic * Driving modality order*	-	-	-	-	1e-4 (7e-5) *
Variance Components					
Level 1					
Within-subjects	4.67 (0.25) **	2.97 (0.16) **	2.77 (0.15) **	2.75 (0.15) **	2.55 (0.14) **
Level 2					
In initial status	95.86 (30.35) *	120.62 (38.25) *	120.64 (38.25) *	120.65 (38.25) *	115.02 (36.47) *
In rate of change	-	-0.77 (0.32)*	-0.77 (0.32)*	-0.77 (0.32)*	-0.69 (0.30)*
Covariance	-	0.01 (3e-3) *	0.01 (3e-3) *	0.01 (3e-3) *	0.01 (3e-3) *
AIC	3291.36	3029.08	2984.93	2981.49	3109.482

Note. Model 1=Unconditional means model; Model 2=Linear growth model; Model 3=Quadratic growth model; Model 4=Cubic growth model; Model 5 = Cubic growth model with Driving modality order; AIC=Akaike's Information Criterion.

*$p < 0.05$.
**$p < 0.001$.

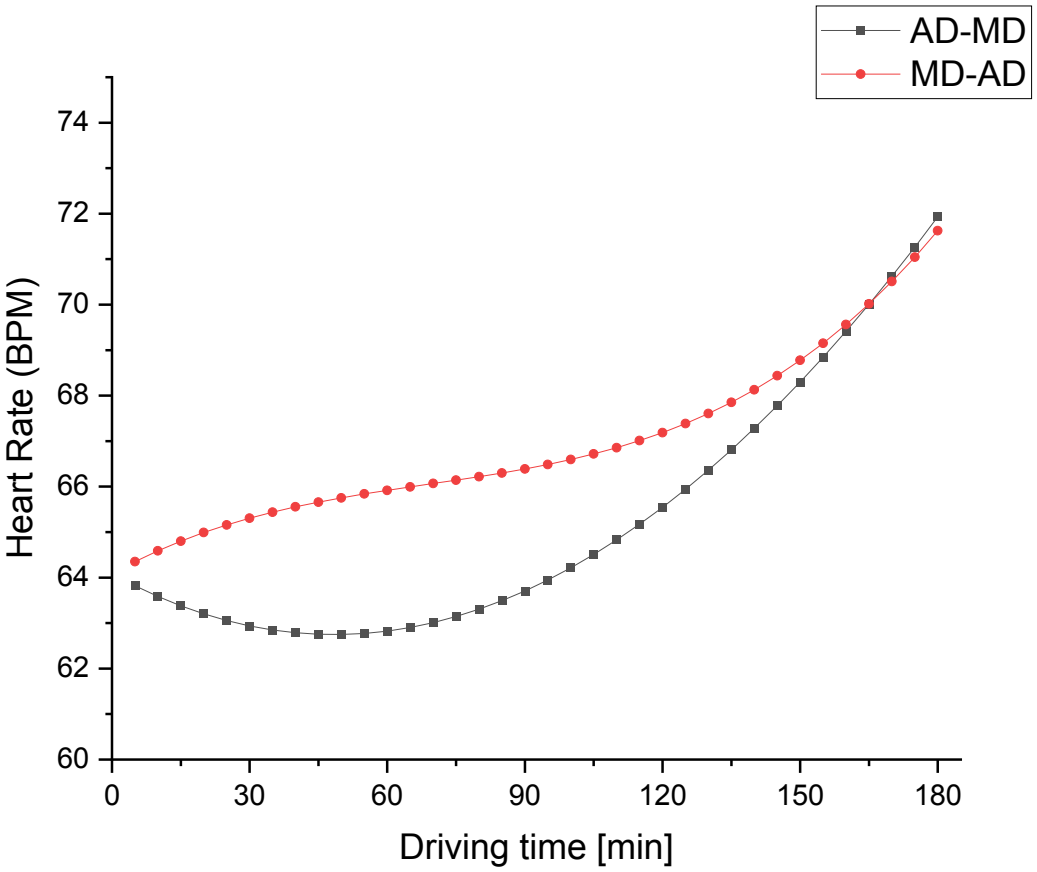

Figure 3. *Effects of driving time (time on task) on Heart rate. The dotted red curve represents the trajectory of the nasal skin temperature over the 3-h driving session in MD-AD group. The black curve represents the trajectory of Heart rate in AD-MD. The 90-minute time point represents the moment of the change of driving mode.*

4.5 Discussion

Driving fatigue is a critical factor in road safety management. Understanding its implications on driving performance is essential for developing effective prevention strategies and reducing the number of road accidents. Several factors can contribute to the occurrence of a state of reduced alertness, which can result in slowed reflexes, increased reaction times and physiological changes while driving (Soares et al., 2019). Physiological monitoring could provide real-time information about the driver's state, even in low-arousal conditions. The main aim of this work was to assess the validity of physiological indices in detecting arousal changes in driver fatigue condition. More specifically, we sought to explore the effects of fatigue on the driver's arousal state by monitoring cardiac and thermal activity. As illustrated above, exposure to a monotonous driving scenario for three hours and more is the fatigue induction paradigm commonly used in the literature (Li et al., 2009; Kee et al., 2010; Fu et al., 2016). In our study, in order to induce increasing levels of fatigue, we replicated the prolonged driving scenario by introducing an additional new element, which was the driving mode—manual or autonomous. Autonomous driving is anticipated to be the predominant mode of transportation in the future. Investigating its impact on physiological parameters may provide insights into its implications for driver capabilities, particularly regarding the ability to regain control of the vehicle when necessary. Thus, the full sample was divided into two groups balanced according to the starting order of driving mode. Our goal was to evaluate the impact of fatigue, resulting from extended driving time duration, on the driver's physiological responses and to investigate how the driving mode might modulate these effects. To obtain a much better understanding of how fatigue could be affecting levels of arousal while driving, we examined how nasal skin temperature (nasal tip) and heart rate changed across a 3-h monotonous driving simulated session. On the basis of previous knowledge, our initial hypothesis was that drivers with difficulty staying alert due to the prolonged time on task would exhibited increased nasal skin

temperature and decrease cardiac activity. Hence, considering the thermographic findings, no relevant variations in nasal tip temperature were observed over time in the MD-AD group. However, in the AD-MD group, a very slight increase in nasal skin temperature was observed during the first hour of driving. This temperature gradually decreased after one and a half hours, followed by another slight increase toward the end of the task. In certain aspects, these results align with findings from previous research (Diaz-Piedra et al., 2019). In the study conducted by Diaz-Piedra and colleagues, participants were exposed to 2 hours of monotonous simulated driving scenario in manual mode, during which their nasal skin temperature was monitored. A 3-degree increase in the temperature of the tip of the nose was observed during the first 75 minutes of driving and then gradually decreased. Although the initial increase in temperature is similar, our results showed a very minimal variation compared to this study, likely due to the experimental task. In our study, participants in the AD-MD group were engaged in a passive autonomous driving task for the first experimental hour and a half, which only required them to monitor the road, and this may have attenuated the arousal response associated with fatigue. Nevertheless, a noticeable gradually drop in nasal tip temperature was observed during the transition to driving manual mode, and this decrease remained stable until nearly the end of the task. This might suggest that the shift to the active driving task (i.e., manual driving) may have modulated the driver's arousal response levels, as reflected in the changes in skin temperature trends. Aside from thermographic analysis, we have used electrocardiography to monitor any changes in driver’s cardiac response (i.e., heart rate) while performing the prolonged task. Overall, a change in heart rate trend due to driving time was evidenced in both groups. Regardless of the driving mode, a slight and gradual increase in heart rate was noted after one and half hour of driving, and such effects persisted throughout the driving task for the remainder of the activity. Contrary to our expectations and the current literature, in our results we did not find any clear evidence of a physiological deactivation response due to fatigue

induced by driving time, usually observed as decrease in HR and increase of its variability. Indeed, several studies have shown a decrease in cardiac autonomic indices (i.e., heart rate and HRV indices) after more than two hours of driving, presumably due to a state of fatigue resulting from the prolonged driving period (Liang et al., 2009; Schmidt et al.,2009; Lecca et al., 2022). However, our study included a change of driving mode after 1.5 hours and this may have influenced the perception of prolonged driving time. In fact, the few studies on driving fatigue available in the literature only exposed participants to manual driving and no one has studied autonomous driving mode, especially in fatigue conditions. Therefore, autonomous driving or driving mode shift may have contributed to mitigating the effects of fatigue on physiological parameters classically observed in paradigms with prolonged monotonous driving.

In summary, the results of our exploratory study suggest that physiological detection methods such as thermal infrared imaging and cardiac activity monitoring could both provide a valid, reliable, real-time, and non-invasive measure of changes in arousal, in driving fatigue paradigms included.

4.6 Conclusions

Investigating the causes and finding effective solutions to tackle the issue of driving fatigue has become a topic of international interest in both academia and industry. As mentioned above, operating a vehicle in low arousal states can compromise the safety of the driver and other road users, especially due to the impair in available attentional resources under fatigued conditions. The implementation of non-invasive physiological measurement tools for the monitoring of driver status would facilitate a more comprehensive understanding of the phenomenon and its manifestations, thereby enabling the development of more targeted interventions. The main aim of our research was to assess validity of physiological indices, such as nasal skin temperature and heart rate, in detecting changes in in arousal levels during 3-h monotonous driving, a common scenario for

inducing fatigue while driving. Differently from existing literature, our study included both autonomous and manual driving modes to evaluate how these conditions might modulate the driver's physiological response to fatigue from prolonged driving. We expected to observe a decrease in driver physiological activation (i.e. increased nasal skin temperature and decreased cardiac activity) as an effect of fatigue induced by time on task. Conversely, our results showed no evidence of physiological deactivation due to fatigue from driving time. The use of autonomous driving or changing driving mode mid-activity may have contributed to mitigating the effects of fatigue on physiological parameters classically observed in paradigms with prolonged monotonous driving. However, although not in the expected direction, both physiological indices showed a change in trend over time, suggesting that physiological detection methods such as infrared thermal imaging and cardiac activity monitoring could be considered as measures valid, reliable, real-time and non-invasive measures of arousal changes, even in driving fatigue paradigms. Study limitations included collecting data from a small sample size and a lack of equitable sex representation, thereby limiting our ability to find associations between individual characteristics and thermal and cardiac autonomic responses. Further investigations with larger sample sizes and sex balance could reveal an association between sex and physiological parameters during driving fatigue, which did not assess in this pilot study. Moreover, it would be beneficial to incorporate additional psychophysiological (e.g., heart rate variability [HRV] indices) and behavioural parameters (e.g., driving performance indices, such as steering behaviour, lateral lane positioning, braking and acceleration position) into the analysis. In summary, our results add to the current literature by examining thermal and cardiac autonomic activity during driving fatigue and emphasise the importance of considering variables that may be part of our near future, such as autonomous driving. Autonomous driving, especially at levels above level three, could in future represent passive activity for the driver, as highly automated vehicles do not require driver intervention in most (levels

three and four) or all circumstances (level five). Understanding the impact that prolonged driving in autonomous mode can have on the driver's psychophysiological state can be crucial for the development of these vehicles. In other words, monitoring the driver's condition during long driving time in autonomous mode could provide valuable insights into the optimal duration of its use and the driver’s ability to regain control of the vehicle when necessary. Ultimately, psychophysiological investigations of drivers under various conditions can help to clarify the underlying causes and identify the most effective parameters for capturing the subject's state during the performance of a dynamic and complex activity such as driving. This information could be used to develop sensors for human-vehicle interaction systems or enhance autonomous driving technology.

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CHAPTER 5. – Brief summary and general discussion

The present project sought to investigate in depth an activity that millions of people perform every day to reach work and social points of interest: driving a vehicle. Driving a vehicle is a complex and dynamic action, requiring the joint involvement of perceptive, visuospatial, attentional, motor and decision-making skills. Loss of any of these functions or altered psychophysiological state can increase the risk of making driving mistakes, resulting in an increased risk of traffic accidents. As illustrated, several factors can influence driving behaviour to the point of reducing vigilance and alertness at the wheel and compromising safety for the driver and other road users. Several studies have shown that internal factors (i.e., emotions, mental workload, sleep quality) and external factors (i.e., road conditions) can interfere with safe driving. Moreover, socio-demographic characteristics could explain heterogeneity outcomes in driving behaviour (i.e., sex, driving experience). It is well known that affective state and the level of mental workload influence the physiological state of the subject. Under conditions of stress, increased workload or fatigue, a series of neurovegetative responses, mediated by the autonomic nervous system (ANS), are elicited. Therefore, the use of peripheral biomarkers such as HRV and infrared thermography can be useful in revealing the driver's physiological state, both under fatigue and drowsiness and under stressful conditions while driving. Due to the high number of road accidents, there has been a growing interest over the years to better understand the causes that can impair efficiency at the wheel and to develop strategies to support drivers and increase road safety. In particular, many industrial and academic players are developing solutions that include the development of environmental and road technologies, driver assistance technologies (e.g., ADAS), the design of cars with different levels of driving automation, and even autonomous driving. In addition, examining the psychophysiological implications during driving could prove useful in the design of intelligent sensors to be implemented in human-vehicle interaction systems. The main goal of this thesis was to explore and monitor the

driver's physiological state in both real and simulated driving context and to examine the effects of various factors, both environmental and human, that can potentially cause changes in driving behaviour and alter the driver's psychophysiological state. In other words, we examined whether and how factors such as the driver's perceived levels of stress, mental workload and fatigue, or environment (e.g., road type) could modulate his/her autonomic response while driving. Furthermore, a number of technologies currently being developed to improve driving safety were presented in this project. For example, the European NextPerception project aimed to develop a complex driving monitoring system capable of detecting driving fitness and suggesting effective intervention strategies for the driver ((Nextperception, 2020). Moreover, through the Internet of Things (IoT) paradigm, an in-vehicle monitoring architecture has been proposed that could be useful in detecting information on the overall driver's health status thanks to the technology of several interconnected devices (Davoli et al., 2016, Davoli et al., 2022, Mattioli et al., 2024). These are examples of how automotive research is moving, which are trying to integrate physiological knowledge with major technological developments. Therefore, the principal goal of this thesis was pursued in the belief that it would be useful to gather evidence on what happens physiologically to the driver in the contexts of mental stress or fatigue, in order to be able to use this information to better develop and define driver assistant systems. Consequently, this work presents three studies aimed at gaining a deeper understanding of the relationship between the driver's physiological responses and driving actions in various potential risk conditions.

In the **second chapter**, a pilot study on monitoring the driver's physiological state in a real driving context was presented. In view of existing literature on environmental (e.g., road type) and individual (e.g., sex, driving experience) factors as modulators of driving behaviour (Dwight and David, 1997; Hill and Boyle 2007, Healey and Picard, 2005; Westerink et al. 2008; Montgomery et al., 2014; Cordellieri et al., 2016), an experiment was designed to examine the driver's cardiac

autonomic response to potentially stressful external stimuli in an ecological driving environment. The experimental idea arose from the fact that few studies have monitored stress-related cardiovascular autonomic activity during a real driving task, especially with a passenger in the vehicle, acting as an external stress factor. In fact, most of these studies adopted mental workload induction tasks not closely associated with daily driving activities. Thus, we wanted to test a more realistic method to induce stress or increase mental workload in the subjects and observe their autonomic cardiac response while driving. Furthermore, we were interested in assessing sex and driving experience as potential explanatory factors in the different psychophysiological response to driving. We used several measurement tools to assess the driver's psychophysiological state, including HRV analysis and various psychometric instruments. We expected to observe physiological variations depending on the road conditions and traffic flow and an increased stress response as a function of unpredictability of the route and the exposure to comments on the participant's driving style by the passenger researcher. HRV analysis on the full sample revealed significant overall autonomic activation while driving, independent from the exposure to external stressors, sex, driving experience and habitual driving behaviours. A significant positive correlation emerged between anxiety-stress symptoms and aberrant driving behaviour. In summary, our results suggest that the overall driving task produced a notable impact on cardiac autonomic neural modulation. These results are in line with those highlighted in the study discussed in chapter three. The second study described in this thesis (**Chapter three**) aimed to evaluate the effect of mental workload due to distractive tasks on the driver's physiological state during a simulated driving task. As has been well demonstrated, distracted driving can compromise driver safety and secondary activities while driving can increase the driver's workload, decreasing the attentional resources needed to control the vehicle. Among the most recognised causes of distracted driving behaviour is the use of devices such as mobile phones, which implies a visual and cognitive distraction that results in a reduced

ability to supervise the environment outside the vehicle (Svenson et al., 2005; Amini et al., 2023; Strayer et al. 2006). Using a safe and well-controlled simulated driving experimental environment, it was possible to manipulate the driver's workload by exposure to different tasks that were to cause interference, a distraction from the primary driving task. For instance, among the distractive stimuli included in the experimental protocol was the use of the mobile phone to examine a common distraction behind the wheel. In other words, the use of the device was included as a cognitive and visual distraction factor. Aside the mobile phone, other distracting stimuli were used to determine an increased perception of distress in the driver, such as tasks that required working memory and attentional resources during the driving. As described in the chapter, these stimuli were presented sequentially in order to increase the demand for attentional effort during the driving task over time. Therefore, we were interested in examining whether the increase in the complexity of distractive tasks simultaneously revealed an increase in the stress response while driving. In this specific study, environmental factors (e.g. traffic conditions) were controlled, as participants were subjected to a simulated low-traffic highway driving scenario. As in the study described in chapter two, we investigated sex as a potential explanatory factor in the different physiological response to driving. Overall, the results of the study revealed significant overall autonomic activation while driving, regardless of exposure to the amount and different conditions of distraction and sex.

Although the two studies just described differ methodologically and procedurally, they had the same scientific objective, which was to study the effects of driver workload on neurovegetative parameters during a driving task. In both simulated and real driving studies, external solicitations were used to evaluate the interaction between mental workload and physiological driver response. On the one hand the experimenter with comments and directions in a real urban context, on the other hand a series of distractive stimuli during the simulated primary driving task. The results of both studies indicated that there were no notable changes in the driver's cardiac autonomic

response to these external stimuli added to the driving task. For example, contrary to the existing literature, in the real road study environmental factors did not influence the driver's physiological outcomes. No different arousal response was observed as a function to the road context (i.e., ring-road vs urban road) in which the driver was performing the task. Indeed, several studies have demonstrated that a higher traffic density could modulate the perception of workload and the driver's physiological response. It emerged that city driving was more stressful than highway driving (Bitkina et al., 2019; Tavakoli et al., 2020). Furthermore, the researcher's comments during urban driving did not increment the driver's workload, which did not lead to an increased stress response during psychosocial stress phases. As in the first study, the addition of secondary distractive tasks to the primary driving task did not result in an elevated stress response in the second study. These results are not in line with the existing literature, which has shown that dual-tasking can modulate the driver's cardiac autonomic response (Brookhuis and De Waard, 2010; Lenneman et al., 2009; Collet et al., 2009; Kass et al., 2007). The results of the two studies could be explained by the nature of the experimental settings and procedures. On the one hand, it is possible that the experimental route used in the real road study was not sufficiently stressful to elicit a greater physiological response, despite the inclusion of urban driving in the experimental procedure. Secondly, driving in an urban context was already an attentional resource demanding task, and it could be that the driver did not beware to the experimenter's comments, but only to road directions and supervision of the road driving environment, and this could explain the lack of an additional stress response to the task. On the other hand, in the second study, it is possible that the exposure of the participants to different types of tasks, for too short limited time, did not result in a strong and clear physiological response to driving distraction. In addition, the simulated driving environment may have contributed to limiting the real effects of distracted driving, as it may be perceived as less immersive and truthful. In any case, interesting results emerged from both the real and simulated study. HR

significantly increased and HRV (RMSSD) significantly decreased compared to baseline conditions, with such effects persisting throughout the driving task. More specifically, we observed a sharp change in HRV once participants began driving and this finding is in line with previous research (Lee et al.,2007). Overall, these results suggest that driving has a significant impact on cardiac autonomic neural modulation, also demonstrating that peripheral biomarkers such as HRV are useful for monitoring and providing information on ecological and everyday situations such as driving activity. Consequently, in **Chapters 2 and 3**, the factors (i.e., mental workload and stress) that can influence driving behaviour and lead to physiological changes associated with a state of high arousal are discussed. Furthermore, the concluding study of this thesis **(Chapter 4)** explores a phenomenon that can negatively impact driver health, manifesting as a state of reduced arousal, or fatigue, while operating a vehicle. Fatigue is considered to be the main cause in road traffic accidents, as it makes the driver more vulnerable to the road environment, especially due to the reduction of available attentional resources in such circumstances (Soares et al., 2019; Zeng et al., 2024). It can exhibit due to various internal causes (i.e., poor sleep quality, overload of an individual's cognitive resources) and might be exacerbated by external environmental factors such as driving duration or the quantity of stimuli present in the road framework (Di Stasi et al., 2015; Aidman et al., 2015). It is no coincidence that the most commonly used fatigue induction paradigm in drivers involves exposure to a prolonged and monotonous driving route**.** Thus, as in the two studies previously described, using physiological measures could enhance our understanding of the phenomenon and help identify which psychophysiological indicators may be useful for detecting changes during everyday activities like driving, even in fatigue conditions. The main aim of our research was to assess validity of physiological indices, such as nasal skin temperature and heart rate, in detecting changes in in arousal levels during 3-h monotonous driving, a common scenario for inducing fatigue while driving. Differently from existing literature, our study included both autonomous and manual driving modes

to evaluate how these driving modality conditions might modulate the driver's physiological response to fatigue from prolonged driving. Consequently, the sample was divided into two groups according to the starting order of driving mode. We expected to observe a decrease in driver physiological activation (i.e. increased nasal skin temperature and decreased cardiac activity) as an effect of fatigue induced by time on task. Conversely, our results showed no evidence of physiological deactivation due to fatigue from driving time. The use of autonomous driving or changing driving mode mid-activity may have contributed to mitigating the effects of fatigue on physiological parameters classically observed in paradigms with prolonged monotonous driving. However, although not in the expected direction, both physiological indices showed a change in trend over time, suggesting that physiological detection methods such as infrared thermal imaging and cardiac activity monitoring could be considered as measures valid, reliable, real-time and non-invasive measures of arousal changes, even in driving fatigue paradigms.

In summary, the various studies presented in this thesis have sought to highlight the factors that could potentially influence behaviour while driving, with the primary aim of exploring comprehensively the driver's psychophysiological state, both in high and low arousal conditions. Further research is needed to better understand the relationship between physiological state and intrinsic characteristics of driving activity and intervening factors. Importantly, it could be useful to incorporate additional psychophysiological (e.g., pupillometry, EEG) and behavioural parameters (e.g., driving performance indices, such as steering behaviour, lateral lane positioning, braking and acceleration position) into the analysis. Although no differences were highlighted in the studies included in this thesis **(chapters 2 and 3)**, exploring in more details the socio-demographic characteristics in driving behaviour could reveal an association between sex/driving experience and psychophysiological response during driving. Furthermore, the significant correlations between psychological and behavioural characteristics of driving (i.e., higher levels of anxiety/stress

symptoms were associated with a higher tendency to commit errors and violations) resulted in **chapter 2** suggest the importance of considering drivers' psychological conditions when studying their behaviour and implementing strategies to improve driving performance.

In conclusion, this thesis adds to the current literature by examining psychophysiological activity while driving in both real and simulated driving environments. It emphasises the importance of considering the psychophysiological approach as a valid method in the field of driving, with the potential to add useful knowledge for the development of biometric sensors that can be applied to monitor the driver's state and, through artificial intelligence, manage risk situations related to distraction, fatigue or emotional states while driving.

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Appendix - Joint Driver-Vehicle Emotional Status Classifier

This chapter contains a part of a work that has already been published “Mattioli, V., Davoli, L., Belli, L., Gambetta, S., Carnevali, L., Sgoifo, A., ... & Ferrari, G. (2024). IoT-Based Assessment of a Driver’s Stress Level. Sensors, (17), 5479.”

Introduction

Over the last five decades, research activities focusing on the impact of driving tasks on the psycho-physiological status of a driver have gained an increasing scientific interest. Indeed, driving can be considered a major experience in many people’s life. Instances of early works on this topic mainly focus on the relationship between traffic congestion and stress (Stokols et al., 1978; Gulian et al., 1989; Hennessy et al., 1997), demonstrating that conditions of high congestion are associated with higher levels of perceived stress. However, driver stress may also be influenced by other external factors (e.g., roadway conditions, weather, visibility, etc.) and internal factors (e.g., sex, age, personality, etc.) (Hill et al., 2007). Moreover, it has been demonstrated that the driving context (e.g, road objects, signs, vehicles, etc.) has a significant impact on the driver’s status (Tavakoli et al., 2023). Attempts to characterize the driving context from driver behaviour have been carried out in (Moosavi et al., 2017), where car trajectory segmentation is exploited to derive meaningful characteristics of the driving context. Hence, both external and internal factors may negatively affect the driving performance by altering the psycho-physiological status of the driver, possibly causing road accidents and dangerous situations. This further motivates the development of advanced monitoring systems able to extract and process physiological parameters to evaluate the psycho-physiological activation of a subject as a response to the driving task. Indeed, the perception of stressful stimuli causes a psycho-physiological reaction in the human body by altering its functions. In particular, physiological processes are regulated by the Autonomic Nervous System

(ANS), which is composed of the sympathetic and parasympathetic systems (Waxenbaum et al., 2023). A psycho- physiological activation corresponds to the activation of the sympathetic system, which regulates body functions in stressful conditions, and a simultaneous deactivation of the parasympathetic system, which regulates body functions at rest. In this work, we refer to the psycho-physiological activation of the driver with the term *arousal*.

Among different indices that might be observed, an important informative physiological index of the stress level of a subject is the heart rate variability (HRV), which can be defined as the beat-to-beat temporal fluctuation in heart rate (HR) (Van Ravenswaaij-Arts et al., 1993). In particular, the HRV reflects the activity of the ANS, which may be influenced by stressful stimuli and/or mental efforts. Moreover, HRV can be inferred from an ElectroCardioGram (ECG) and has been considered in various research works in the context of driver stress detection (Healey et al., 2005; Riener et al., 2009; Munla et al., 2015; Liu et al., 2023; Ahmed et al., 2021). An extensive review of works where the HRV is considered as the main physiological parameter used to detect stress in different contexts can be found in (Kim et al., 2018). This review provides evidence to support the use of the HRV for the objective assessment of physiological stress. Further examples of works, which highlight the reliability of the HRV as stress indicator, are (Kim et al., 2008; Chen et al., 2019), where it is demonstrated that mental stress can be inferred from HRV analysis.

Given the importance of the HRV as a stress indicator, several attempts at developing driver assistance systems (DASs) based on the monitoring of physiological parameters of interest have been proposed in the literature. For example, in the study by Athanasiou and colleagues (2014), a DAS equipped with a stress monitoring system was designed to provide assistance in electric vehicles by intervening with the vehicle speed in case of anomalies (Athanasiou et al., 2014), whereas, in the study by Siam and colleagues (2023), a Machine Learning (ML)-oriented stress detection system to be possibly integrated with a DAS is presented (Siam et al., 2023). Both systems

presented are based on the analysis of ECG signals and other physiological data, including skin temperature (among others). Indeed, variations in the skin temperature of a subject can be considered another important stress indicator. In particular, the skin temperature on the nasal tip region is regulated by the ANS and has been observed to decrease in the case of high levels of stress (Matsuno et al., 2018). Therefore, thermal imaging- based systems able to detect facial skin temperature variations have been developed in simulated driving environments (Engert et al., 2014; Aloui et al., 2022; Diaz-Piedra et al., 2019). In general, the extensive analysis carried out in the literature on the use of HRV and facial skin temperature to estimate the stress status of a subject proves how these two physiological parameters are considered significant indicators of stress by the research community.

On the basis of these remarks, the design and implementation of an advanced in-vehicle Driver Monitoring System (DMS) able to collect and jointly process physiological data, including HRV signals and facial skin temperature variations, to evaluate the arousal level of the driver, are presented. More in detail, the proposed DMS is composed of interconnected heterogeneous sensors properly interacting according to different Internet of Things (IoT)-oriented technologies. In particular, wireless communication protocols, such as Wi-Fi and Bluetooth Low Energy (BLE), and standard messaging protocols, such as the Message Queuing Telemetry Transport (MQTT) protocol and Transmission Control Protocol (TCP)-based sockets, are exploited to collect physiological data extracted by a wearable sensor and a thermal camera integrated in the system.

In-Vehicle Monitoring Architecture

The proposed DMS is composed of heterogeneous sensing and processing devices that should properly be positioned inside the vehicle cabin and connected with each other. For the sake of clarity, the experimental system setup is shown in Figure 1, where the various components and their interactions are shown. In particular, a wearable sensor and a thermal camera are employed to gather physiological parameters of interest and record facial skin temperature variations in the driver, respectively. Additional vehicular data might be extracted by embedded inertial sensors, i.e., an ECU located on board the vehicle. The processing component in the proposed DAS is an Intel Next Unit of Computing (NUC), acting as a Wi-Fi Access Point (AP), providing a private Wi-Fi network, and also providing networking, storage and processing functionalities for the entire system.

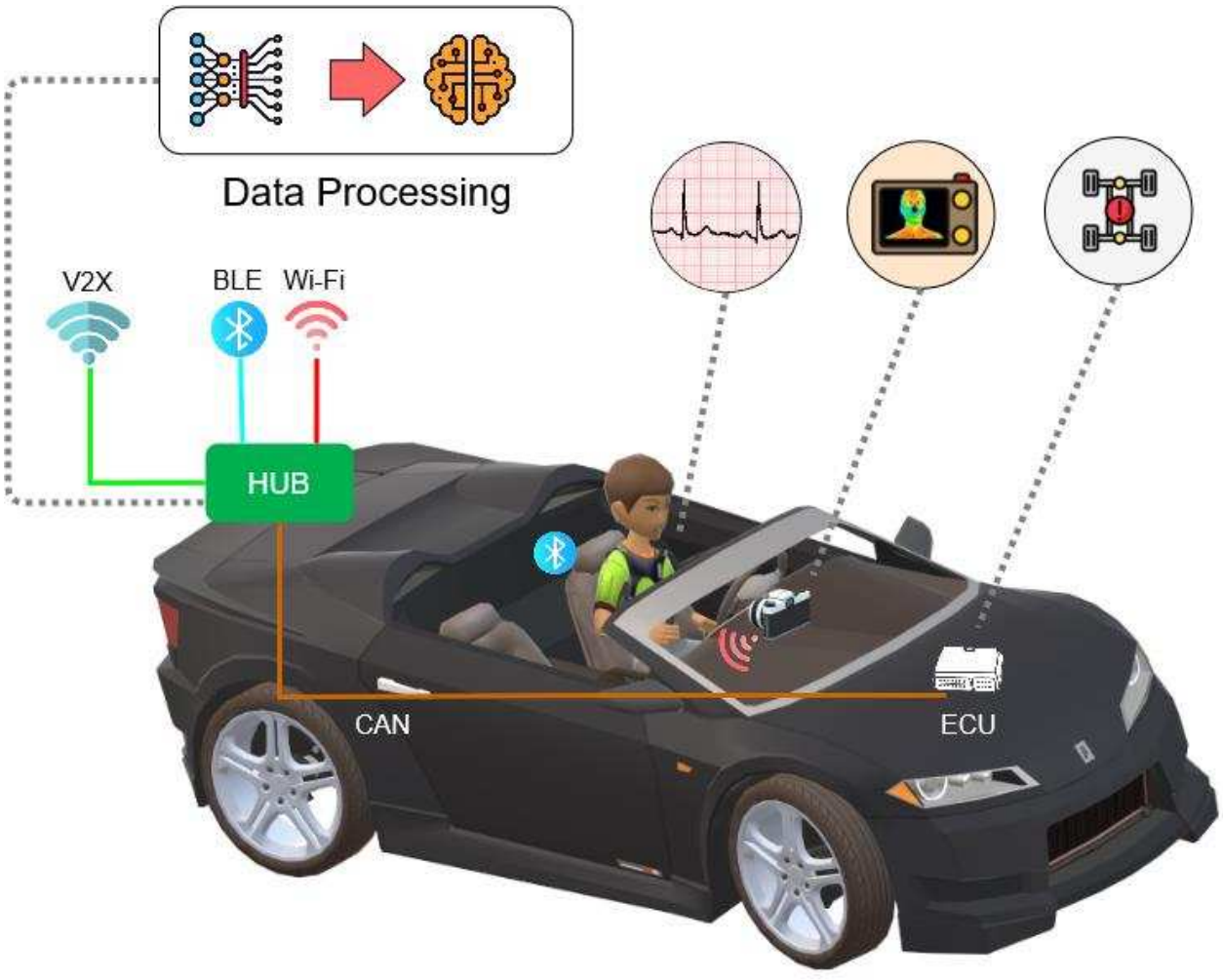

Figure 1*. Experimental setup of the proposed DMS.*

Wearable Sensor

In order to collect physiological data from the driver, an Equivital EQ02 Life Monitor device (manufactured by Equivital, Cambridge, UK) is employed (Equivital, 2023). In detail, the Equivital EQ02 Life Monitor is a wireless wearable sensing device capable of recording multiple vital signs related to a subject wearing the sensor, and is composed of two elements: (i) a textile bodice embedding electrode, i.e., the EQ02 Sensor Belt, and (ii) a EQ02 Sensor Electronics Module (SEM). The SEM can capture biological signals in real time, including ECG and respiratory signals and other indices such as HR, respiratory rate (RR) and skin temperature. Additional information on the body position and motion can be collected from a 3-axis accelerometer embedded in the SEM. Moreover, the SEM is equipped with a Class-1 Bluetooth interface for real-time data transmission. Alternatively, the acquired data may be logged on the sensor and *a posteriori* downloaded. Pictures of the EQ02 Sensor Belt and SEM are shown in Figure 2a and Figure 2b, respectively, whereas their correct on-body positioning is illustrated in Figure 2c. As can be seen, the SEM needs to be inserted in a specific pocket on the left side of the belt itself. Thus, this wearable device can be considered *non-invasive* since it is made of a flexible fabric that can easily adapt to the body of the driver. Owing to its wearing comfort, this device is also employed by athletes and workers during their regular activities.

a

b

c

Figure 2. *Equivital EQ02 Life Monitor sensor: (**a**) belt, (**b**) SEM, and (**c**) positioning.*

The second component integrated in the architecture of the proposed monitoring system is a FLIR One Pro LT thermal camera (manufactured by Teledyne FLIR LLC, Wilsonville, OR, USA), which allows us to collect thermal information from specific regions on the body of the driver (namely, the face and nose) and from the surrounding environment (Teledyne FLIR LLC, 2023). This device is composed of an RGB sensor and an infrared sensor, allowing us to simultaneously capture visible and thermal images or videos, respectively. Data may also be acquired according to a blended modality, providing a combination of visible and thermal outputs. On the practical side, the FLIR One Pro LT thermal camera has to be connected to a smartphone as an external USB Type-C "dongle" and may be managed by either Android-or iOS-like mobile applications. The smartphone and connected thermal camera dongle need to be accurately installed inside the vehicle cabin to guarantee optimal positioning for data acquisition. To this end, a fair trade-off between recording quality and positioning obtrusiveness should be considered, since further video processing and analysis tasks require a frontal perspective. Then, similarly to the wearable sensor, this device can also be considered non-invasive since it does not require direct contact with the subject and is positioned unobtrusively, without limiting the road view. For the sake of illustration, the connection

of the FLIR dongle to the smartphone and their positioning inside the cabin are shown in Figure 3a and Figure 3b, respectively. An illustrative example of a captured infrared video frame is shown in Figure 3c. Finally, we highlight that the thermal camera has small dimensions (namely, 68 × 34 × 14 mm), making it easily positionable by means of a standard phone car holder attached to the front windscreen of the vehicle, as shown in Figure 3b. Hence, thanks to this simple positioning, the thermal camera can be considered as not distracting and/or stressful for the driver.

a

b

c

Figure 3. *FLIR One Pro LT thermal camera: (**a**) sensor connection, (**b**) positioning, and (**c**) recorded infrared frame.*

Data Acquisition Architecture

The different modules and composing the proposed driver monitoring architecture transmit their collected data to the central hub, namely, the Intel NUC running Windows 10, located on board the vehicle and intended to work as a multi- interface gateway for data storage, fusion and processing. A pictorial representation of the data acquisition architecture of the proposed DMS is shown in Figure 4, where the connections between the different components are highlighted and the central hub is denoted as the Joint Driver–Vehicle Status (JDVS) module.

With regard to the interconnection of the sub-modules, standard communication protocols are employed. In particular, the EQ02 SEM sends physiological data (i.e., the HR, HRV and RR of the subject wearing the wearable bodice) through its Class-1 Bluetooth interface to the JDVS module, where the Equivital eqView Pro desktop application is installed and collects the physiological data. These data are then forwarded to a TCP socket toward an internal Python application (running on board the JDVS module), hosting a TCP server and listening for incoming packets for further processing. On the other hand, thermal data recorded by the FLIR One Pro LT thermal camera are transmitted (by the smartphone hosting the FLIR dongle), exploiting the MQTT protocol, to the JDVS module through the private Wi-Fi network hosted and advertised by the JDVS itself. To this purpose, an Android-based mobile application, denoted as MoniDrive (as shown in Figure 4) and running on a Huawei P20 Lite smartphone, was developed to acquire RGB, thermal images and additional frame and camera information (i.e., temperature scale, framed hottest and coldest points, etc.) through the FLIR camera connected on its USB-C interface. Finally, serial communication channels, such as the Controller Area Network (CAN) bus, might also be exploited to transmit vehicular data from an ECU.

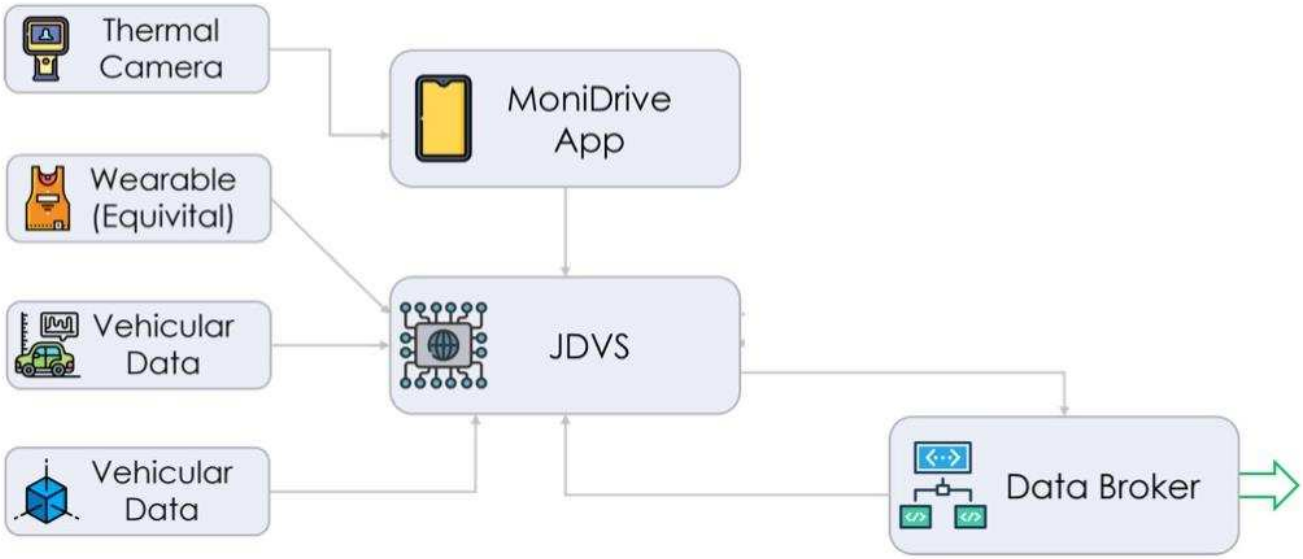

Figure 4. *Data acquisition architecture of proposed DMS.*

We remark that vehicle vibrations do not affect the data acquisition phase. In fact, the employed wearable bodice is not sensitive to small vibrations. Moreover, the proposed video processing techniques allow us to detect a framed face regardless of the camera position and orientation, with the subject's facial temperature not being affected by vehicle vibrations in any way. As a consequence, in-vehicle vibrations occurring during the driving activities do not represent a noise source in the experimental data collection phase. The JDVS module asynchronously processes the data received from the various components (every 1 s from the wearable sensor and every 5 s from the thermal camera, respectively) in order to produce an arousal index (denoted as ϕ) in the range [0, 1], where 0 and 1 indicate null and maximum physiological activations.

To summarize, the operational tasks performed by the JDVS module are the following:

• Acting as a Wi-Fi AP (advertising a private Wi-Fi network) and as a MQTT broker;

• Processing the information received from the MoniDrive app, through innovative image and video processing algorithms that will be detailed later;

• Processing the data received from the sensorized belt;

• Performing data fusion to estimate the arousal ϕ and transmit it to external interested entities (e.g., the vehicular ECU through a parallel Ethernet or Wi-Fi interface).

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“The mind is not a vessel to be filled, but a fire to be kindled”

Plutarch

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