Understanding Drivers' Stress and Interactions With Vehicle Systems Through Naturalistic Data Analysis

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Abstract—Today, and probably for a long time to come, humans will remain an integral part of vehicles for driving tasks. Therefore, it is essential to understand how vehicles and drivers interact with each other and how drivers' behavior and physical and mental states affect vehicle performance and traffic safety. This article explores the relationship between driver and vehicle in real-world driving conditions by analyzing large-scale naturalistic data collected from cars and drivers. Specifically, more than 800 hours of driving data from 16 drivers were collected using three different data sources (telematics data, video frames, and physiological data) and two types of analysis were done. The first one analyzes different types of driver-vehicle interactions during driving. The second one investigates the effect of different driving conditions on drivers' stress and explores the relationship between driver and vehicle in different driving conditions. Our experimental results show that drivers' physiological signals are correlated with some variables from vehicle kinematics and influenced by drivers' behavior inside the vehicle. These findings could be used to help manage comfort-related in-vehicle intervention systems and could provide a continuous measure of how different external conditions (traffic, road, weather, etc.) affect drivers.

Index Terms—Vehicle driving, intelligent vehicles, emotion recognition.

I. INTRODUCTION

IT MAY take decades before most cars on the road are fully autonomous, and until then human beings will remain an integral part of the driving task. Driving behavior strongly impacts traffic safety and causes the vast majority of traffic crashes. According to the US National Highway Traffic Safety Administration, more than 6.7 million accidents were reported in the USA in 2018 [1], and around 20-30% of all crashes are caused by unsafe or distracted driving [2], [3].

Hazardous driver states are induced by either physical/physiological (e.g., fatigue [4]) or mental (e.g., anger)

conditions while driving. These conditions may be intrinsic (e.g., stress) or extrinsic (e.g., adverse traffic/road conditions or adverse weather). Perhaps the most infamous hazardous driving states are distractions caused by secondary tasks performed while driving [5], such as eating/drinking, using cell phones [6], talking with passengers, interacting with in-vehicle technologies such as car consoles, radio, or navigation systems, etc [7]. Also, difficult driving conditions such as close surrounding vehicles and adverse traffic or weather conditions can lead to mental stress, impacting the driver's behavior.

Therefore, vehicles must be designed by taking into account drivers' comfort, safety, and adaptability with the vehicle systems. It is likely that human-centered, artificial-intelligence-based systems e.g., an in-vehicle automated intervention system, will play a critical role in monitoring and analyzing driving behavior and activities inside the vehicle in real-world conditions and providing valuable information to drivers and manufactures.

To design an effective intervention system, drivers' physical and mental state and their interactions with the internal and external environment of the vehicle's need to be better understood, modeled, and incorporated into the system design. There have been several studies that examined driving behavior and mental states in different conditions to generate key behavioral insights. However, many of these studies [8]–[11] has used self-reported driver reports, police-reported crashes, and/or questionnaire surveys in their analyses, due to the unavailability of real-world driving behavior data until very recently. Moreover, much of the research [12]–[14] to date has been done either on simulators or in an obstructive and controlled environment with repeatable conditions with known factors. Therefore, there is a great need for naturalistic driving datasets that can provide the mental and environmental context of a given driving event.

Thanks to the rapid technological advancements in telematics, it is now possible to collect and analyze real-world microscopic driving behaviors generated by naturalistic driving systems. "Naturalistic driving" refers to the characteristic of driving in natural conditions, unaffected by any structured experimental design or measurement process. These data are typically collected from various sources such as physiological measurements from biometric wearable sensors, vehicle telemetry data from in-vehicle sensors, and audio/video data [15] that can capture various aspects of driving.

Although driving-behavior modelling using naturalistic driving data is not new, the links between microscopic driving behavior and drivers' mental state in real-world environments

are still not well explored. Current safety systems utilize vehicle dynamics (using telemetry data) but remain unaware of environmental context and driver state, and do not adapt to the changing mental conditions of the driver. Moreover, the naturalistic data considered in most studies were collected with very small number of drivers.

The primary aim of this article is to study and understand (i) the drivers' mental state in different environmental conditions, and (ii) drivers' interactions with in-vehicle systems by analyzing the heterogeneous naturalistic data from a variety of sensors. Such analysis allows us to understand how real-world driving conditions and the driver-environment interaction correlate with driving stress, which is paramount for designing a driver assistance system for improved traffic safety.

The major contributions of this study are as follows:

- We design our experiment to monitor drivers' activity and physiological reactions during real-world driving situations under normal conditions. To fulfil these requirements, we gather the microscopic driving behavior data from vehicle telemetry signals (GPS, speed, acceleration, etc.) using the Controller Area Network (CAN) bus, drivers' physiological data from biometric markers (HR, electrodermal activity (EDA)) using wearable devices, and drivers' activity inside cars from grayscale videostream (including depth images) using 3D cameras.
- We analyze the video data to identify the drivers' activities and interactions with different car components (e.g., steering wheel, seat belt, and car console) to gain insights that can be used for vehicle interior design for better user comfort and experience. Moreover, we analyze the video data with the telemetry and biometric data to understand the effect of drivers' activities on their stress.
- We analyze the biometric and vehicle telemetry data to understand the correlations between stress and microscopic driving behavior at trip level.
- We also explore the feasibility of indirect approaches (both positive and negative) for stress estimation in real driving conditions (e.g., weather, road-type, day of the week), based on the telemetry signals.

The rest of the paper is organized as follows: Section II summarizes the literature on driving behavior analysis, particularly on naturalistic driving data. Section III discusses the data collection and characteristics. We propose the methodology with our analysis in Section IV, before finally concluding the paper with a discussion in Section VI.

II. RELATED WORK

Several studies [9], [16]–[21] have been conducted to monitor and study drivers' physical and mental states in different environmental and traffic conditions. The literature on traffic safety reveals mainly two fundamentally different approaches [22] that offers useful insights into various aspects of driving behavior. The first approach is the drivers' self-report or questionnaire [8]–[11] that leverages the explicit and tacit information held by drivers about their driving behavior, the surrounding traffic, and their vehicle. The other approach, which has been developed in recent years, is collecting and analyzing naturalistic driving data to understand detailed driving behavior in real traffic conditions. The former approach might be less objective as different drivers might report a similar experience differently. Therefore, since our analysis is based on naturalistic driving data, we restrict our discussion to this second type of approach.

There have been several efforts on driving stress estimation from naturalistic driving data. Healey et al. [23], [24] presented data collections methods to monitor stress level in real-world driving conditions using physiological sensor signals e.g., EDA, Electrocardiogram (ECG), Electromyogram (EMG), and respiration. The results in this study showed that skin conductivity and HR show the highest correlation with driver stress level and that the stress levels could be classified into three levels i.e., low, medium and high, with an overall accuracy of 97.4% using 5-minutes interval or data. Rigas et al. [25] presented a methodology based on the dynamic Bayesian network to predict drivers' stress level produced in some specific driving events such as overtaking, hand-breaking, and cross-road. Specifically, they extracted two features, HRvB (Heart rate variation from baseline) and MFAD (EDA mean of first absolute differences), from ECG and EDA data respectively, found that both the features are non-correlated with the stress. Further, they obtained 31-94% accuracy range in classifying stress levels into three different categories i.e., No Stress, Low Stress, Medium-High Stress. Although the study was performed in real-world driving conditions, only one subject was involved. Many studies [26]–[28] found that HR variability (HRV) can be applied to detect driving stress in real-world driving conditions.

Rodrigues et al. [29] presented a non-intrusive prototyping system for continuous monitoring of driving behavior. Observed variables included ECG sensor data, vehicle location, speed, acceleration, fuel consumption, pedal position, and temperature. Thus, the framework was also suited for identifying potential dangerous locations on the road network in addition to characterizing driving behavior. They identified that heart rate variation and acceleration can be related approximately through a quadratic polynomial. The testbed in this framework was not designed to detect individual stress factors.

Sathyanarayana et al. [30] presented a context-aware activity safety system to model the driving behavior utilizing CAN bus signals. To segment the CAN bus data into meaningful parts, a multimedia data annotation tool, UTDAT, was developed which used video channels (driver and road scene videos), driver's speech and CAN bus signals. The analysis of multi-sensor data was performed to identify several driving events (e.g., right turn, lane change, stop) and secondary tasks while driving such as driver talks, silence, music play, navigation instruction. They achieved approximately 93% accuracy for generic maneuver recognition by applying a simple FFT based approach on vehicle speed, brake pedal pressure, and steering wheel angle. Also, the average driver distraction detection performance in their study was always above 70% for all maneuvers. Authors in [30] identified the need for biometric signals, such as those used in this study, to better detect abnormalities in driving.

Darzi *et al.* [31] examined whether the cause of a drivers' hazardous state can be identified automatically from vehicle kinematics, driver characteristics, and physiological measures. During the data collection, drivers were exposed to four causes of hazardous states i.e., sleep deprivation, adverse weather, cell phone use, and high traffic density, and four physiological signals, eight vehicle kinematics signals, and three self-reported driver characteristics (personality, stress levels, and mood) were obtained. Then, different classifiers with all possible feature combinations were employed to identify the cause of a hazardous state from the data. Specifically, sleep deprivation (drowsy vs. alert), traffic density (low vs.high), cell phone use, and weather conditions (snowy vs. sunny) were classified with highest accuracy of 98.8%, 91.4%, 82.3%, and 71.5%, respectively. The data in this study were collected in simulated driving setting.

Qiu *et al.* [32] studied the relation between driver maneuvers and physiological signals (heart rate, breath rate, and EDA) during naturalistic driving recordings. They observed statistically significant deviations in typical physiological responses during maneuvering. Moreover, they reported 72.8% average F1-score for maneuvers classification. This study suggested that fusing CAN BUS data with physiological data, as done in this paper, can give better insights about driving activities.

In [33], Bitkina *et al.*quantified the relationship between driving stress and traffic conditions, and driving stress and road types, respectively. In their study, EDA signals for a male driver were collected in real-world driving conditions for one hour per day for 21 days, and then two separated models were developed to classify stress level (low vs high). This study reported 80.3% accuracy based on the traffic congestion information and 82.9% accuracy based on the road segments. Links between real-world driving stress and driving volatility were examined in our previous article [34] by analyzing 0.2 million geo-referenced temporal samples of real-world driving behavior and health bio-markers from 150 driving sessions.

Mok *et al.* [12] presented a study, called "Wizard of Oz", that was conducted to gain insights on how drivers and automated vehicles interact with each other. This study was conducted in a driving simulator where participants drove through a simulated course and various road and terrain conditions. In this qualitative study, insights in the five areas were discovered: drivers' desire for share control, transition in driving mode (manual and auto), response latency (time for a car to respond), addressing requests (requests performed by car), and drivers' trust in the car. Friedman *et al.* [35] presented a methodology and underlying principals governing the design and operation of an advanced vehicle technology (AVT) for large-scale naturalistic driving data collection from semi-automatic driving vehicles. This study, called MIT-AVT, only focused on hardware and software design specifications for large-scale naturalistic driving data collection.

While significant research has been done on analyzing driving behavior and detecting drivers' physiological states (e.g., stress), very limited studies [36] have investigated driver-vehicle interactions and their effects on drivers' stress in real-world driving conditions. In fact, most of the studies on driver-vehicle interactions [13], [14] and driver emotion has been done either on simulators or in an controlled environment. Unlike existing studies that use either physiological measurements, CAN-BUS data or video data or two of them, we collect and analyze all three types of data in our analysis. Next, we discuss the dataset and methodologies considered in our analysis.

III. DATASET

A. Data Collection

This section describes the collected dataset and the fusion algorithm used to merge the different data streams. A total of 15 million samples have been collected during a real-world driving experiment in Germany. This experiment involved eight vehicles and 16 drivers (including 25% female drivers) for a total of more than 800 hours of driving. The average age of the drivers was 34 years with 8 years of standard deviation. The average driving experience was approximately 15 years (based on the assumption of obtaining a driving license at 18 years old, as common in Germany). Among them, 12% drivers had $0 - 3$ years of driving experience in Germany.[1]

Three main data sources were used to collect the numerical data: (i) wearable biometric devices to measure the physiological signals coming from drivers; (ii) CAN bus loggers to gather telematics data coming from vehicles; and (iii) two 3D cameras located inside the vehicle to record drivers' activity.

1) Biometric Data: Biometric data was collected from each driver using wearable smartwatches (E4 wristbands manufactured by Empatica). These wearable devices offer real-time physiological data acquisition, wireless connectivity, and data storage. In particular, each device is equipped with the following four sensors:

- EDA sensor, to measure electrodermal activity (EDA) that refers to the variation of the skin's electrical conductance in response to sweat secretion. Skin conductance can be a measure of emotional response. This signal was sampled at $4\,Hz$ and expressed in microsiemens (μS).
- 3-axis accelerometer, to measure acceleration data for capturing motion-based activity. This data was collected with a sampling frequency of $32\,Hz$.
- photoplethysmograph (PPG) sensor, to measure the blood volume pulse (BVP), from which the average heart rate (HR) is derived. This signal was sampled at $64\,Hz$. The time between individuals heart beats was also extracted from the BVP signal.
- infrared thermopile, to measure skin temperature.

As the HR from the PPG data was correctly estimated after some seconds of data recording, the measured values of the HR were delayed by 10 seconds in the data collection. Consequently, as these estimated values might suffer from initial estimation errors, we decided to discard the first minute of HR data from each recording session in our analysis. Additionally, wearable sensors can lose skin contact and can provide erroneous measurements. Therefore, the HR data were filtered according to the thresholds values reported in [37].

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[1]A sample of the dataset is available at: https://bit.ly/3lZHkR3

2) Telematic Data: To collect the driving and vehicle's related data (telematic), an on-board diagnostic (OBD-II) data logger connected to the CAN bus was used. The Controller Area Network (CAN) bus is a serial communication bus standard that allows microcontrollers and devices to communicate with each other in a vehicle. The CAN bus data collected in our study consists of 10 different signals: latitude, longitude, altitude, 3-axis acceleration, steering wheel angle, brake and gas pedal positions, seat belt, and ignition signal. Most of these signals were directly linked to the driver's activity and decisions such as harsh breaking, sharp turn, extreme acceleration. GPS data (latitude, longitude, altitude) allows us to track the driver's position and contextualize our analysis with additional data. In particular, OpenStreetMap (OSM) was used to extract the following additional metadata for each GPS point:

- road type: we used the OSM "Highway" property to identify the type of road, street or path.
- maximum Speed: "Maxspeed" key was used to retrieve the maximum legal speed limit for general traffic on a particular road.

Further, we computed the distance of a vehicle from the nearest intersection in the road network. We used the Open Street Routing Machine (OSRM) [38] to detect the intersections in the road network and estimate from which segment the driver was approaching the intersection.

3) Optical Data: Driver's activity inside the vehicle was recorded using two 3D (RGB-D) cameras mounted inside the car, one mounted on the windshield facing the driver frontally, the other mounted on the driver's right-hand side facing them laterally. Each 3D camera provides simultaneously two data streams: a grayscale video stream, and the corresponding depth map (the depth of each pixel in the grayscale frames) that contains information related to the distance of the scene objects' surfaces from the camera's viewpoint. The camera mounted on the windshield facing the driver has been installed with the purpose of monitoring the remaining part of the interiors of the vehicle that are not included in the recordings from the main camera. Specifically, it only provides an additional point of view on the backseats and it has been used only for counting the total number of passengers in the vehicle.

For each session, the grayscale data and the depth maps were recorded as 224×171 pixels, 16bbp (bits per pixel) video stream at 5fps (frames per second) using a CamBoard Pico Flexx camera [39]. Each pixel's depth value ranges between 0 and 16 384 unit, where 16 384 represents the most distant (4 m) possible depth value and 0 the closest depth value (0.5 m). After the recording, drivers faces has been automatically obfuscated for privacy reasons.

B. Data Pre-Processing and Data Fusion

Given the variety and dishomogeneity of the data sources, a preliminary data prepossessing was performed to handle different data related noise/errors such as removing out-of-range values and erroneous GPS coordinates. The next step in the data analysis was the fusion of the heterogeneous data collected from the three different data sources. This process can be divided into three parts: timestamp normalization, timestamp synchronization, and temporal join.

1) Timestamp Normalization: In many cases, the timestamps were reported in different formats and time-zones, so they were converted into Unix timestamps.

2) Timestamp Synchronization: To align and synchronize the biometric, telemetric, and optical data, all three datasets were resampled at 5 Hz using a median filter without applying any interpolation method. After the re-sampling process, we fixed any temporal misalignment and we discarded those samples for which the three dataset were not simultaneously available.

C. Trip Segmentation

Next, we divided the pre-processed datasets resulting from the previous step into trips. Each trip starts when the engine is turned on and ends when turned off. If the ignition signal of the vehicle is not available, we used the vehicle's speed as a proxy: if a vehicle's speed during a trip is 0 or NULL for more than 30 minutes, then the trip was split into two different trips. All the trips were then filtered according to the following criteria:

- A trip should not last less than 5 minutes to avoid external influences in the reported biometric parameters.
- GPS data must be available during the entire trip.
- The total distance covered should be more than 0.5 km.

D. Data Enrichment

In addition to the signals described so far, the dataset was enriched with additional features collected from open source resources or derived from existing signals available in the dataset. Specifically:

- Day of the week and Hour of the day: these additional variable were included in the data from the timestamp.
- Weather: for each location and time in the dataset, the weather information was collected using the DarkSky.io historical weather dataset. The weather information consists of a textual description of the weather conditions for a given location and time.
- Trip duration: computed using the trip's start and end timestamp.
- Longitudinal (frontal) acceleration: as some vehicles were not equipped with any accelerometer, frontal acceleration was estimated using the speed and GPS data.
- Average speed: All the GPS points were partitioned according to a $30 \, m \times 30 \, m$ grid over the different hours of the day, to compute the average speed per cell. This allows us to compare the current speed of the vehicle with the average speed on that road segment and categorize the measured speed as low speed (<30 percentiles), medium speed (30 to 70 percentiles), or high speed (>70 percentiles).
- Start and End of the trip: to identify the drivers' behavior and stress during the beginning and ending parts of the trip, the initial 10% of each trip was tagged as "Start" and the last 10% as "End".

The final dataset obtained contains 15 million records over a period of 383 days from 24 January 2019 to 12 February 2020, divided into more than 2000 trips. The data points distribution is uniform across the different months and it is also equally distributed during weekdays, while we generally have fewer samples during the weekends. From an hourly perspective, the collected data are concentrated around two prominent peaks, 8 AM and 5-6 PM, in accordance with typical commuting hours.

IV. Data Analysis

This section discusses our experimental study to analyze drivers' activity and stress in different conditions. First, we analyze video datasets to extract several events and interpret them with biometric datasets to obtain insights that could help understand drivers' stress and interaction with vehicle systems. Second, we analyze the biometric and CAN bus data to estimate drivers' stress concerning different environmental and driving conditions using association rule mining. Finally, we investigate the relationship between driver and vehicle based on the exploratory analysis on biometric, telemetry, and video datasets.

A. Drivers' Interaction With Car Interior From Video Data

Quantifying the number, the type, and the conditions of events and interactions between a car and driver is an important analysis for making data-based decisions in the design process of its components and features. We nowadays have the technology to do so in large deployments and at a lower cost. However, given the large amount of data collected, it is vital to have an automatic process that extracts valuable information from raw data. This section presents our analysis on high volumes of video datasets to extract drivers' activity and interaction with car interiors that are commonly performed before, during, and immediately after the driving activity; then, we interpret these interactions using biometric datasets.

Car Interior Segmentation: To detect the interaction of a driver with car's interior usage, the car interior was segmented into three parts (area of interests): (i) Seat (ii) Console and (iii) Steering Wheel. Since the camera orientation during a trip remains the same, the interior parts' positions in all video frames for the same trip do not change. Therefore, each part of the car interior (area of interest) was manually labelled.

Driver's Pose Detection: The next step in this analysis is detecting the driver's position. In this regard, we utilized *OpenPose* [40], a Python open-source library to detect the 2D pose of multiple people in an image. OpenPose is a bottom-up pose detection system which can detect a total of 135 vital body points from an image using Convolution Pose Machines (CPM), and what act on hand is called the Hand Detector. CPM network uses CNN models (connected in cascade) which outputs the likelihood map for each pose keypoints in an image. Hand Detector uses the trained CPM network to detect hand keypoints. When a rectangular region containing a hand is fed as input to Hand Detector, a likelihood map is generated for each hand keypoint and coordinates of keypoints with the highest likelihood (as a score) become output. Key-part association is done using part affinity fields (PAF) – two
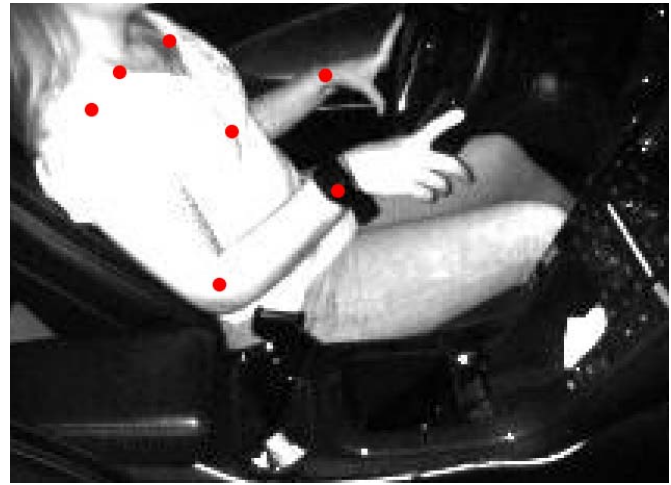

Fig. 1. An example of pose estimation from a video frame using OpenPose [40].

dimensional vectors that encode the position and orientation and of the human limbs. OpenPose produces three distinct pose model. In this work, we use BODY_25 model which can detect 25 different body key points in each frame. (Fig. 1 shows an example of this from a video frame in our analysis).

This approach mainly leverages the 2D component of the video streams. We combined the body key-points provided by OpenPose with the depth maps provided by the 3D camera. In particular, each area in the 2D image that can be recognized as one of the three regions of interest (seat, console, steering wheel) is matched to the depth maps of 3D camera. When something moves closer to a certain part of the vehicle (steering wheel, central console), the values in the depth map change. Such changes can be used to detect driver's interaction with particular parts of the vehicle interior.

In the proposed solution, we leverage the values recorded by the depth camera as a validation of the machine vision analysis. In fact, as the pose detection algorithm might provide false positives under certain conditions (e.g. light, color patterns), a significant variation in the distance measured by the depth camera can be reliably linked to a physical change in the recorded scene. Specifically, the depth resolution reported by the camera datasheet is $< 1\%$ of the measured distance in the 0.5-4m range [39]. In the proposed configuration, the maximum measured distance between the camera and the steering wheel is ~ 0.8m, therefore the maximum error at this distance is < 0.8cm. In this context, the smallest object that we want to detect is the hand of a driver that can be modeled as a ~ 5cm variation in the depth signal, thus generating a change that is significantly bigger than the instrumental error. This effect is clearly represented in Fig. 2(a) where the average measured distance changes from 0.8m (frame 2900, shown with red dot) to 0.72m (frame 3010, shown with red square). It is also clearly visible that the subsequent hand movement (e.g. from frame 3060 to frame 3076) can be easily detected using a peak detection algorithm, In this case, we used the Python function find_peaks_cwt from the Scipy library that can find peak(s) in one-dimensional array using wavelet transformation. Finally, if a significant variation is detected,
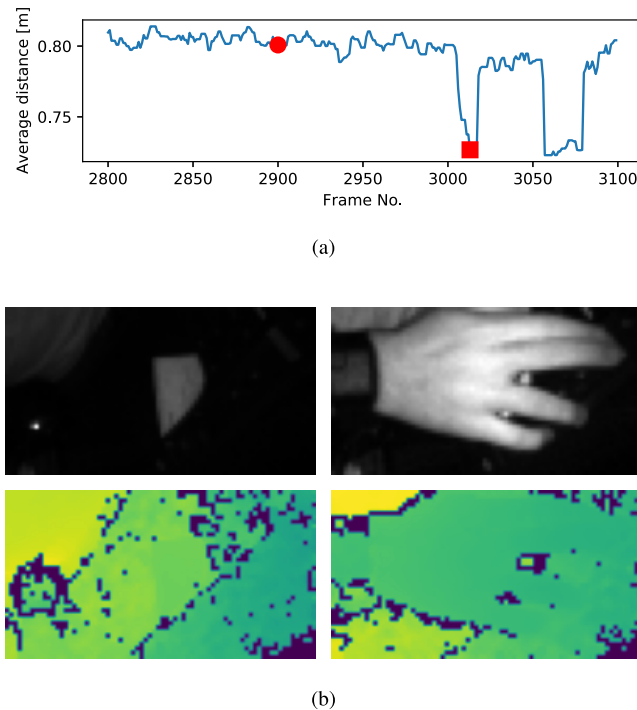
(a)

(b)

Fig. 2. Analysis of a depth video stream. The x-axis shows the frame numbers (in time order) and the y-axis reports the average of all the values of distance (depths) reported by the 3D camera for a selected region of interest.

(a)

(b)

Fig. 3. Analysis of drivers' interaction with the main console. Events counts are plotted against trip time (a), and vehicle speed (b).

the pose detection algorithm is used to validate the position of the hands of the driver. Based on the coordinates of the joints, we recognize if the hands are close to a labelled part of the vehicle or not.

For each trip in the dataset, events such as adjustment of the driver seat, or a driver's interaction with the console or the steering wheel, were recorded and stored in the dataset. The duration and frequency of these events are then used to extract driving behavior patterns that are further analyzed jointly with the driver's stress level. Below we discuss our analysis of the drivers' interactions with different parts of the vehicle interior.

1) Interactions With the Main Console: Drivers' interactions with the main console have proven to be more frequent when the vehicle travels for an extended period at a constant speed. To detect drivers' interactions with the main console, we localized the driver's hands in the video frames and computed their distance from the central console using the depth values. If the hand is at a distance less than 5cm from the console, we tagged the hand's position as "console".

An interesting quantity to measure is the distribution of these interactions over time. Fig. 3(a) reports the distribution of the drivers' interactions with the main console, where x-axis represents time (in minutes) since the trip starts, and y-axis represents the number of interactions with the console. We note that while the first interaction happens most likely at the very beginning of the trip, all subsequent interactions follow a clear decreasing trend in time. This information is important to understand the driver's attention during the trip and better design the interaction-management of a car with the driver. To understand these interactions during driving, we also computed the distribution of interactions (with console) over the vehicle's speed, as shown in Fig. 3(b). We observe that
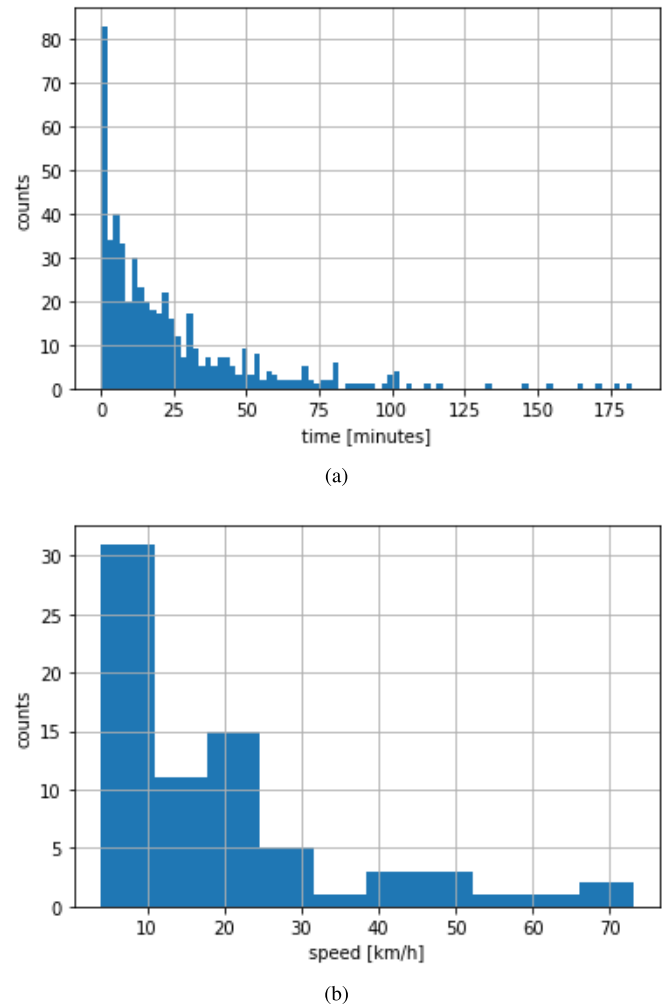
most of such interactions happen at very low speed. Changing the type of interaction required or nudging to the driver depending on the vehicle speed could be a new frontier for better safety or more natural user experience.

2) Interactions With the Seats: We detected drivers' interactions with seats in a similar way as we detected main console interactions. Fig. 4 shows the distribution of the number of adjustments of the driver's seat position over time. Most of the seat adjustments were carried out at low speeds. Moreover, since the vehicles were shared among different users during data acquisition, most of the seat adjustments were recorded when there was a change of driver.

Due to the relatively small size of this experiment and the less frequent occurrence of this kind of interaction, we could not further analyze and validate the effect of external conditions that caused seat adjustments. However, this methodology could be applied to larger deployments to better understand the real usage of the seat adjustments. Knowing the conditions when a driver adjusts the seat during a trip can show interesting phenomena that could be measured by a real-time system that can actuate on the seat anticipating the driver's actions, especially with micro-adjustments or small changes.
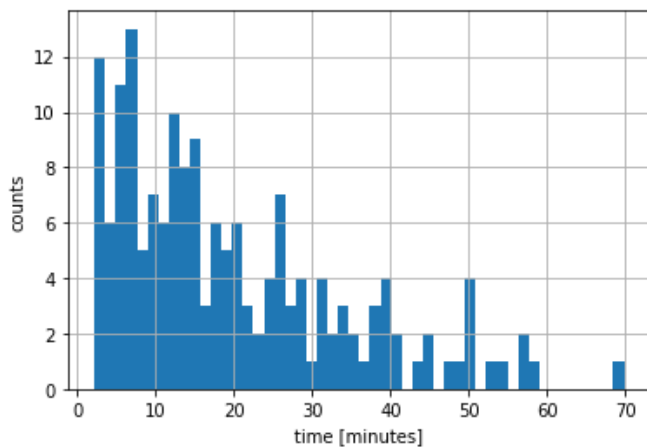
Fig. 4. Analysis of drivers' seat interactions. Seat adjustment events are plotted against trip time.
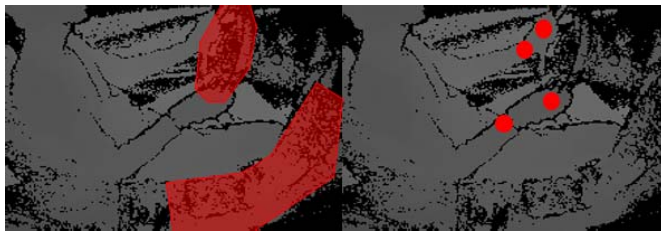

Fig. 5. An example of a driver's interaction with the steering wheel identified from a video frame.

3) Interactions With the Steering Wheel: Different interesting patterns may emerge from the driver's interactions with steering wheels. We detected the hands' positions in each video frame (from the lateral camera) and identified their interactions with steering wheels. Fig. 5 shows an example of a driver's interactions with the steering wheel, detected from a video frame. We estimated that on an average 76% of the total trip duration a driver had both hands, on 20% the trip only one hand, and on 4% of the trip had no hands on the steering wheel. The latter case was much more frequent when the vehicle was stopped at intersections or traffic lights. We also analyzed the car's speed during such interactions and observed that the average speed of the car while using both hands was 15% lower than the average speed measured while the driver was using only one hand. This is probably due to a more relaxed driving style while driving on faster roads.

B. Understanding the Relations Between Driver and Vehicle

The second part of this analysis focuses on understanding more profound relations between the driver and the vehicle, by analyzing the data collected from cars (from CAN bus) and drivers (biometric and videos). Since changes in HR variability and electrodermal activity have been successfully linked to stress by several studies in the literature (see Section II), we focus our analysis on those two quantities.

1) Correlation Between Can Bus and Biometric Signals: To understand the relations between driver and vehicle dynamics, we computed the correlations between CAN bus and biometric data variables. Given the natural differences between individuals, the biometric signal range may be different. Therefore,

the biometric signals were normalized between -1 and 1 and used in the correlation analysis. Fig. 6 shows the correlation matrix for CAN bus and biometric variables. Some relations in the CAN bus and biometric data were trivial and were used to validate the quality of the collected dataset. For example, there was a positive correlation between the electrodermal activity and the ambient temperature as the skin's ability to thermoregulate itself has an impact on the skin conductance and the electrodermal activity. Another positive correlation was shown between the length and the duration of a trip. Vehicle speed and throttle are also positively correlated. The x and z-axis of the accelerometer on the wearable device show some degree of correlation as certain orientations of the wearable devices are more common than others such as the angle between the hands and the steering wheel during driving.

A very interesting correlation was observed between vehicle speed and driver's HR. We found a negative correlation between the HR standard deviation and the speed of the vehicle. We can interpret this relation stating that a higher speed is usually correlated to a more relaxed driving experience; however, to better interpret this correlation, more analysis is provided in the following section.

Fig. 7 shows the distribution of HR (as a surrogate for stress) in our dataset. With the mean HR 84.26, the distribution of HR was right-skewed, indicating that a sizable portion of the driver's instantaneous HR does not fall in the normal range (60 bpm – 90bpm). Fig. 8 depicts the relationship between instantaneous speed and longitudinal acceleration. The patterns in Fig. 8 intuitively suggest lower magnitudes of instantaneous longitudinal accelerations at higher speeds (> 75 km/h) as well as smaller variations (or volatility) in acceleration/deceleration values.

The relationship between driving stress with longitudinal acceleration revealed new meaningful patterns. Fig. 9 shows the distribution of longitudinal acceleration against HR (stress), where a negative correlation has been found. Most data points lie in the normal range, i.e., normal longitudinal acceleration with normal HR. However, significant contrasts were also observed, such as extreme longitudinal accelerations/decelerations with normal driving stress (HR). Similarly, there were driving instances with normal longitudinal accelerations/decelerations with extreme driving stress. In other words, despite a weak overall negative correlation (R-value = -1.5), extreme values of longitudinal accelerations and HRs are relatively rare. These findings are important and may suggest compensation theory effects or driver sensation-seeking behavior, i.e., drivers may already be under stress so they may be extra cautious in their driving behavior.

2) Effect of Driving Conditions on Driving Stress: The ultimate goal of this analysis is to derive some simple rules that can be used to estimate driver stress in different driving conditions and behavior. Two different classes of stress were identified: positive stress (eustress) and negative stress (distress). The positive stress is characterized by lower levels of EDA and higher levels of HR. For the negative stress, instead, we consider high levels of EDA and higher HR, as reported in [41].
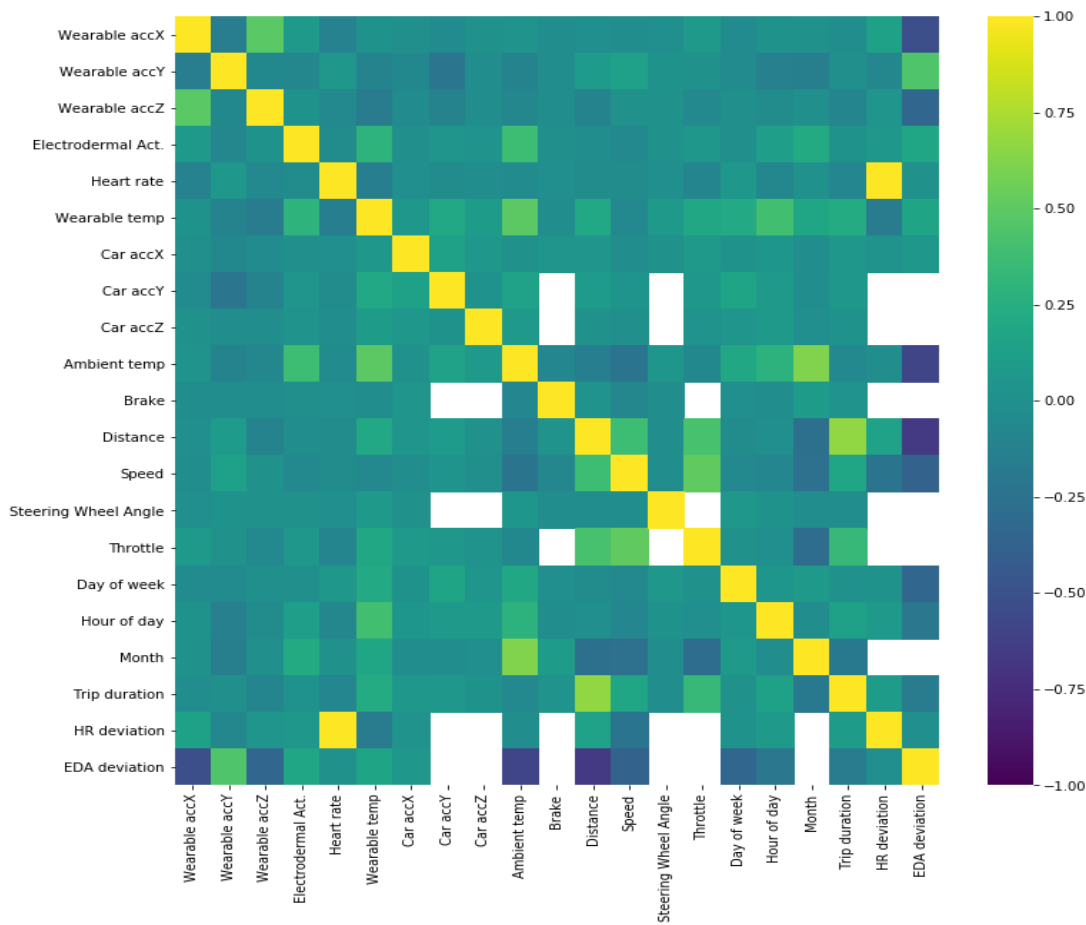
Fig. 6.   Feature correlation analysis.
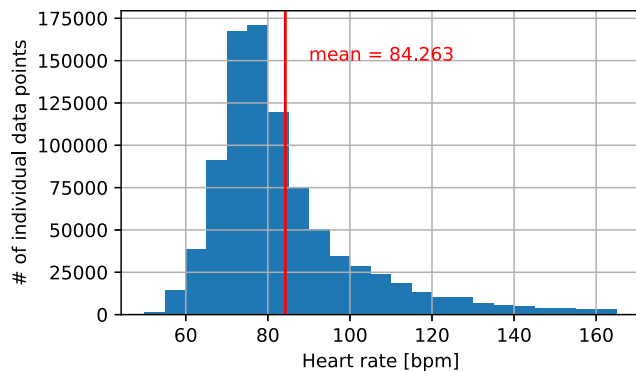

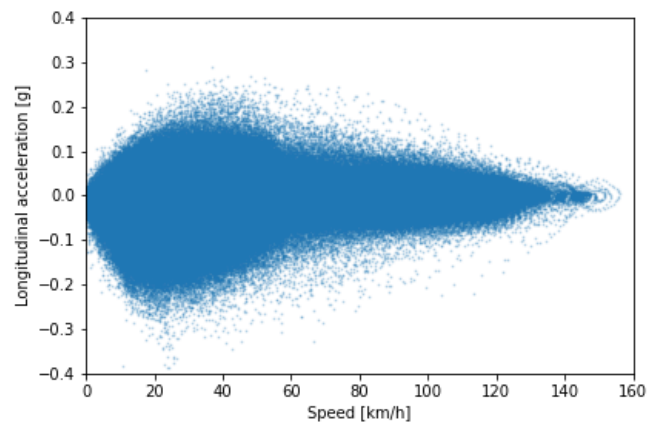Fig. 7.   Distribution of driver heart rate.

Fig. 8.   Distributions of speed with respect to longitudinal acceleration.

Most of the work in the literature on this topic are based on self-reported questionnaires. In this analysis, we detect the conditions (antecedents) that can generate stress (consequent) by applying the *frequent pattern* (FP) growth association rule discovery algorithm on the collected dataset. Unlike Apriori algorithm, FP algorithm can discover most frequent and relevant patterns in a large dataset, without candidate generation. This algorithm represent the data in the form of a suffix tree structure, called FP tree, which maintains the association between the itemsets. In this analysis, FP algorithm generates all the frequent set of events (itemsets), *conditions* → *stress*, according to the minimum "support" and "confidence"

defined by the user. The "support" defines the probability, $p(conditions \cup stress)$, and "confidence" level represents the conditional probability that an event having *conditions* also has *stress*, $p(conditions/stress)$. We use minimum support and confidence as 0.07 and 0.70, respectively to identify frequent set of events. The results from this analysis are reported in Tables I and II as a set of events that co-occur with positive or negative stress levels, respectively. We notice that most of the events that are detected by the association rules have
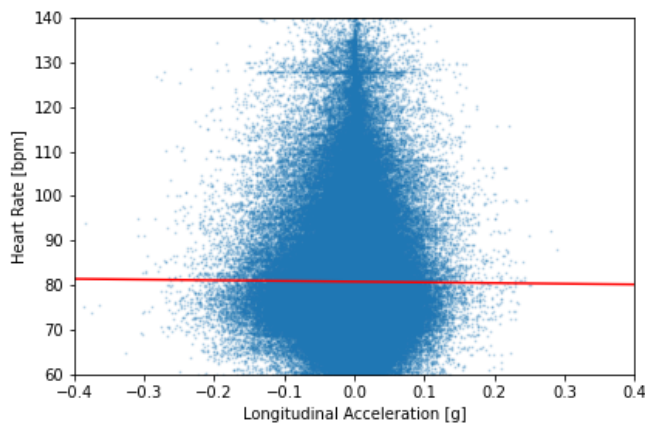
Fig. 9. Distributions of driver heart rate with respect to longitudinal accelerations.

Boxplot grouped by people

Fig. 10. Analysis showing the relationship between stress level (HR) and the number of people in the vehicle.

strong external components. For example, most of the negative stress events happen during the beginning of the week or when the weather is not good. Similarly, most of the positive stress events (excitement) are linked to the weekend or higher temperatures.

Another signal that, according to our analysis, had an impact on driver stress was the number of people inside the vehicle. For each trip, the number of people inside the car were computed manually by visualizing a random video frame while the car was moving. In our dataset, 78% of the time the driver was alone, 18% of the time there was also a passenger and remaining 4% of the time there were three or more people inside the vehicle. In this analysis, as shown in Fig. 10, the average value of the HR was 83.4bpm when only the driver was inside the car, but it reduced to 78.9bpm when there was also a passenger, which further reduced to 76.9bpm when there were two or more passengers. So, we found that an increase in the number of passengers in the car reduces the stress level of a driver ($R = -0.135$). However given the uneven distribution of the samples we could not further analyze and validate this effect.

V. DISCUSSIONS

The main findings of the analysis reported in this study have several important implications for original equipment manufacturers (OEMs), suppliers and researchers. Unlike existing studies that considered either or both of telematic and biometric data, our study involved all three types of data (including video data) in the analysis to obtain more interesting insights. Following are some of them with their practical implications.

- The usage statistics and patterns found offer high value for car and parts manufacturers in the development and innovation process for new products and services in and around the vehicle; while further data would be necessary for a more consistent identification of usage patterns, our collection already shows the potential for such type of analysis.
- The analysis of seating positioning and stress levels can be used to improve car seating and automatic adjustments depending on the identified scene (e.g. as per the set of events derived from the association rules).
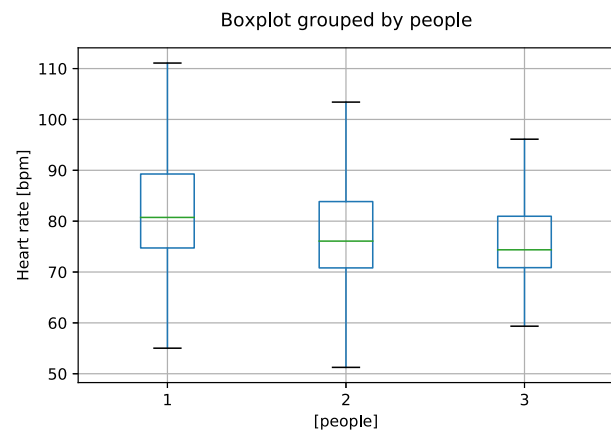
- Within the set of events identified with the association rules, products for the vehicle can be developed that try to shift a negative stressful event into a positive one. E.g., using ambient light to give the driver a more relaxing scene (similar to a clear day which is an item in the set of positive stress) when in presence of a cloudy/overcast day (which is an item in the set of negative stress).
- We found that, on average, the driver initiates the driving activity 3 minutes after entering the vehicle and this is the period when most of the seat adjustments tend to happen. Knowing that the driver tends to adopt a dynamic driving style in stressful situations (a 5% increase in HR in connection with an increase in driver's stance changes was found) a product can be developed around smart seat adjustments to bring the driver to the most comfortable stance.
- From the driver stance analysis, we found a lagged correlation between drivers movements and HR which shows that a lag is present between action and reaction. This indicates that there is room for reactive products development to offer the user what he/she needs before he/she even realizes it.
- During positive stress, the user is usually more prone to engage in other activities as the experiment results demonstrate in the stress analysis and through the computed statistics. This can be used to identify the best timing, in a scene of autonomous driving/shared mobility, for the "car" to offer further functions and services to the user.
- The study indicates that preparation for the trip is an important part of the journey (at least within the experiment sample and particularly for long trips). The different statistics on car usage gives to the stakeholders indications where to focus to create/improve products and safety (the results show that even the driver tends to interact with the phone and infotainment at several scenes/points of the journey).
- Conceptually, this study highlights the predictive associations between driving behavior and stress. For example, given the positive correlation between longitudinal acceleration/decelerations and driving stress, instantaneous

TABLE I
ASSOCIATION RULES FOR POSITIVE STRESS DETECTION (LOW EDA – HIGH HR)

Set of Events	Confidence
19:00, Clear, high ambient temp, high distance	0.97
50 km/h max, Clear, Wednesday, high ambient temp, low distance, low speed, week	0.92
13:00, Overcast, Sunday, high speed, weekend	0.78
13:00, Overcast, high speed, weekend	0.75
15:00, Thursday, week	0.74
16:00, Clear, Wednesday, low distance, week	0.74
19:00, Friday, Overcast, high ambient temp, week	0.72
17:00, Monday, high distance, high duration, low speed, week	0.71

TABLE II
ASSOCIATION RULES FOR NEGATIVE STRESS DETECTION (HIGH EDA – HIGH HR)

Set of Events	Confidence
17:00, Monday, high speed, low duration, week	0.94
17:00, Monday, Overcast, low duration, week	0.88
19:00, Clear, Wednesday, low acc y, low ambient temp, week	0.87
Monday, Overcast, high speed, low duration, week	0.83
15:00, Mostly Cloudy, low duration	0.82
10:00, 30 km/h max, Monday, Mostly Cloudy, low ambient temp, low speed, residential, week	0.78
15:00, Wednesday, high distance, week	0.76
Tuesday, high speed, low distance, low duration, week	0.74
11:00, Overcast, weekend	0.72

driving decisions can be monitored in real-time and warnings can be provided to drivers.

- In terms of method and tools, the study offers a framework for product makers to replicate the study and collect further data on identified potentials.

A. Limitations of the Study

The presented research and experiments in this article are the initial results of our long-term study about driving stress analysis based on different driving activities and surrounding traffic and environmental conditions. Even though our developed framework and presented techniques provide various important findings and insights by fusing heterogeneous naturalistic driving data collected from three different data sources, there are has some limitations that need to be addressed in the future. Although the experiment has been carried out for an extended period of time, a strong limitation is the number and homogeneity of users involved. A broader experiment involving more people from different countries and age groups, driving all across the world, might show behaviours that are region specific. Therefore, the proposed solution should be considered as a pilot experiment to show the potentiality of monitoring the behavior of drivers, rather than a deep dive into the behavior of drivers. An additional aspect that should be better investigated is the contextual surrounding of the vehicle. In this experiment, we analyzed the context by looking at the information available from OSM but the number and positions of other vehicles, the condition of the road, or other volatile aspects that were not considered in this study might play a very important role in generating stress while driving.

VI. CONCLUSION

This article investigated the relationships and interactions between drivers and vehicles in a real-world naturalistic driving observation. Our study collected and analyzed data from three different sources i.e, videos from 3D cameras, telematics from CAN bus, and biometric signals from wearable sensors.

We discussed a methodology for video data analysis to identify drivers' interaction with car interiors. Beyond the quantitative results provided, a major outcome of the presented methodology for video data analysis is the creation of an implementable analysis infrastructure. The presented methodology can be used as a valid alternative to additional in-vehicle sensors, and can add a potential value for future vehicle product development.

Beyond measuring the driver's interaction with the different car's components, the real value of the developed framework is in its holistic approach. The identified interactions acquire additional value when they are extended to estimate the users' behavior and the surrounding environment. These kinds of analyses are crucial with the rise of new design and innovation challenges for disruptive vehicles that can adapt to the different mobility scenarios. For new vehicles, most of the components need to be thoroughly redesigned and re-engineered due to the drastic change of use compared to traditional cars. Therefore, measuring drivers' interactions with the vehicle interior will be a fundamental asset in the design and testing process for new vehicles.

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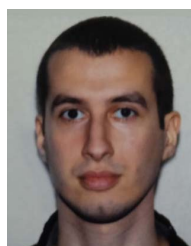
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