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Investigating Cardiovascular Activation of Young Adults in Routine Driving

MD Tanim Hasan, Huda Alghamdi, Salah Taamneh, Mike Manser, Robert Wunderlich, Panagiotis Tsiamyrtzis, and Ioannis Pavlidis, *Senior Member, IEEE*

Abstract—We report on a naturalistic study investigating the effects of routine driving on cardiovascular activation. We recruited 21 healthy young adults from a broad geographic area in the Southwestern United States. Using the participants' own smartphones and smartwatches, we monitored for a week both their driving and non-driving activities. Monitoring included the continuous recording of a) heart rate throughout the day, b) hand motion during driving as a proxy of persistent texting, and c) contextualized driving data, complete with traffic and weather information. These high temporal resolution variables were complemented with the drivers' biographic and psychometric profiles. Our analysis suggests that anxiety predisposition and high speeds are associated with significant cardiovascular activation on drivers, likely linked to sympathetic arousal. Surprisingly, these associations hold true under good weather, normal traffic, and with experienced drivers behind the wheel. The said findings call for attention to insidious effects of apparently benign drives even for people in their prime. Accordingly, our research contributes to intriguing new discourses on driving affect and personal health informatics.

Index Terms—cardiovascular activation, heart rate, sympathetic arousal, naturalistic driving studies, trait anxiety, driving speed, affective computing

1 Introduction

Humans spend increasingly more time using machines for work, entertainment, and other purposes [1]. There is emerging evidence that some of these uses are unhealthy, bearing short- and long-term consequences. As of this writing, the lion share of human-machine interactions is directed toward computers and cars. Everyday, U.S. adults spend nearly eight hours interacting with digital content [2] and over one hour driving [3]. A great deal of research has been done on the physiological effects and health implications of computer use. For instance, several studies investigated the role of screen time on sleep disturbances [4], [5], [6]. Other studies linked extensive screen time with comorbidity arousing from the associated sedentary lifestyle [7], [8]. The research community responded to these sober findings by proposing orthotic designs that would keep track of users' screen time, increasing their awareness [9]. They also fielded imaginative apps intent on luring users away from screens by enticing them into gamified physical activity [10].

In contrast to the physiological effects of daily computer use, relatively little research has been done on the physiological effects of daily driving. There are several possible reasons for that. Until recently, it was challenging to perform naturalistic driving studies. Without such studies, it is difficult to document or even identify the physiological effects of routine driving. Moreover, driving safety has been commanding huge attention in automotive research [11], leaving little room for investigations on less visible issues. Here we present work that uncovers physiological effects of daily driving.

Naturalistic driving studies (NDS) collect vehicle performance and driver behavior data during normal, impaired, and safety-critical situations. The original aim of such studies was through understanding of driver behaviors to craft preventive crash measures, including enforcement policies, infrastructure, and the design of intelligent vehicle systems. NDS research has been converging to the following conclusions: 1) Driver behavior is the major cause of car crashes. 2) Drivers tend to reduce speed and increase headway, as a workload alleviating measure during distracting activity and adverse weather conditions. 3) Smartphones have great potential as data collection devices. 4) Driver behaviors can be improved through feedback. Such feedback can be operationalized with pay as you drive (PAYD), pay how you drive (PHYD), and manage how you drive (MHYD) insurance schemes [12].

Conventionally, naturalistic driving studies were carried out in instrumented vehicles, featuring special data acquisition systems (DAS). A well-known example is the Strategic Highway Research Program 2 (SHRP-2) naturalistic driving study; it is associated with a high frequency and high resolution set that was collected by installing to participants' cars DAS and multiple sensors, such as radars and cameras [13]. The SHRP-2 study design enabled continuous monitoring of driver performance, driver behavior, speed, acceleration, lateral and longitudinal positions, as well as eye glancing behavior. SHRP-2 and other similar studies, however, were lacking physiological channels. Participants included 3,247 drivers from six different states including New York, Washington, Pennsylvania, North Carolina, Indiana, and Florida.

- *M. Hasan, H. Alghamdi, and I. Pavlidis are with the Department of Computer Science, University of Houston, Houston, TX, 77004.*
- *S. Taamneh is with the Department of Computer Science and Applications, Hashemite University, Zarqa, Jordan.*
- *M. Manser and R. Wunderlich are with the Texas A&M Transportation Institute, A&M University, College Station, TX, 77843.*
- *P. Tsiamyrtzis is with the Dept. of Mech. Eng., Politecnico di Milano, Italy and the Dept. of Statistics, Athens Univ. of Econ. and Business, Greece.*

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SHRP-2 features $n = 673$ crashes. Of the said crashes, 8.92% ($n = 60$), 13.22% ($n = 89$), 37.59% ($n = 253$), and 40.27% ($n = 271$) were severe, police-reportable, minor, and low-risk tire strike crashes, respectively. Data analysis revealed that human errors and violations contributed to 93% of the crashes, roadway factors contributed to 17%, vehicle factors contributed in 1%, and 4% of crashes contained unknown factors [14].

In recent years, the idea of using smartphones as data collection devices, instead of costly in-vehicle DAS, has been gaining ground in the NDS community. Smartphone-based NDS are more economical and unobtrusive than conventional NDS, but are not without problems. For instance, due to intensive sensor use during naturalistic driving studies, smartphone batteries tend to drain, resulting in loss of data and upset drivers, who are left with dead phones in the middle of the day. Such problems, however, can be managed and things get better all the time, as smartphone technology continues to improve [15].

Zhang et al. performed one of the first smartphone-based NDS [16]. They used data from the smartphones' GPS, gyro, and accelerometer sensors to classify driving behaviors through support vector machine modeling. To carry out their study, Zhang and colleagues recruited a convenience sample of 14 participants from their lab, and asked them to drive specific cars in pre-defined routes. In another early smartphone-based NDS, Hong et al. tried to understand and model aggressive driving style [17]. Amassing a naturalistic data collection from 22 drivers for 3 weeks, the authors constructed a model that classified aggressive and non-aggressive drivers with an accuracy of 90.5% and 81%, respectively. Importantly, the study concluded that although smartphones are promising data collection devices, they have their limitations. Specifically, the authors found that smartphone GPS signals cannot reliably measure car speed, suggesting that in naturalistic driving studies, smartphones should be paired with on-board diagnostic II devices (OBD2), for acquiring reliable measurements of speed and other vehicle variables.

Early smartphone-based NDS have evolved nowadays into ubiquitous and multimodal NDS, through the addition of smartwatches and freely available information channels, like weather. This latest generation of NDS is exemplified by HARMONY [18], where drivers' behaviors and states are monitored through the following channels: (1) outside and in-cabin video streams that include facial data; (2) physiological signals that include the drivers' heart rate; (3) observational signals that include the drivers' hand motion data; (4) ambient noise, light, and the vehicle's GPS location; and (5) music logs, including song features such as tempo.

The inclusion of smartwatches in ubiquitous NDS enabled the acquisition of heart rate (HR) and heart rate variability (HRV), which can serve as proxies of arousal [19], [20] and potentially stress estimators [21]. This newfound capability, directed the focus of naturalistic driving studies in understanding and mitigating drivers' negative emotions, stress levels, and anxiety. The new thinking is that drivers' psychophysiology is linked to error-prone driving behaviors; thus, psychophysiological indicators can potentially explain car crashes. Tavakoli et al., analyzing the HARMONY dataset, reported that different road objects might be associated with varying levels of increase in drivers' heart rate as well as different proportions of negative facial emotions detected through computer vision. Larger vehicles on the road, such as trucks, are associated with the highest amount of increase in drivers' heart rate as well as negative emotions. Additionally, shorter distances and higher standard deviation in the distance to the lead vehicle are associated with a higher number of abrupt increases in drivers' heart rate, indicating a possible stress increase [22].

Besides multimodal naturalistic studies, more specialized driving studies have also been flourishing in recent years. Such studies are usually focused on driver distractions and rely primarily on video recordings and computer vision methods. The 100-driver study by Wang et al. [23] is a representative example of this genre. Other computer-vision studies on distractions include MDAD [24] and the driver posture study by Abouelnaga et al. [25].

In a parallel line of inquiry, researchers have been investigating poor health outcomes associated with driving. Unlike all the other work we mentioned earlier, research on health effects of driving has been largely based on surveys and spearheaded by scholars outside the computing and engineering communities. In this context, several studies have shown that lengthy car commuting perpetuates conditions that compromise individuals' health. Identified factors included stress caused by traffic congestion, searching for parking, interacting with other drivers, and safety concerns [26]. In fact, some studies showed that commuting has a particularly detrimental effect on the psychological health of women, and this result was robust to numerous different specifications [27].

Recently, health effects of driving have been attracting increased attention among researchers. Meseguer et al. designed an Android application able to monitor in real-time drivers' physiological data and vehicles' diagnostic data. They focused on fourteen different routes accounting for a total driving time of 6 hours and 2 minutes. Their experiments showed that the differences in terms of heart rate between quiet and aggressive driving ranged between 2.5% and 3% beats per minute higher for the latter behavior compared to the former [28]. The implication of this finding is that aggressive driving is not only a negative predictor of safety, but potentially a negative predictor of long-term health. In another health outcomes study, Huynh et al. demonstrated that a significant minority of drivers exhibit hyperarousal in mundane acceleration events, such as stop and go traffic [29]. The authors arrived at this conclusion by conducting a naturalistic driving study, where participants drove the same city itinerary under similar conditions. The observed hyperarousal, termed accelarousal, was measured to be nearly 46% above the participants' baseline, and thus a significant stressor. The authors expressed concerns about the long-term effects of such stressors, if they are experienced daily over the course of many years (e.g., see the case of delivery drivers). In this direction, our overriding concern is that repeat driving patterns, like daily commutes, could hide insidious sympathetic activators. Little work, however, has been done to identify such activators through their cardiovascular or other manifestations.

Indeed, such concerns have medical basis. Chronic imbalance of the autonomic nervous system is a prevalent and potent risk factor for adverse cardiovascular events, including mortality. Any factor that leads to inappropriate activation of the sympathetic nervous system (e.g., aggressive driving) can be expected to have an adverse effect, while any factor that augments vagal tone tends to improve outcomes. Chronic sympathetic hyperactivity increases the cardiovascular workload and predisposes to endothelial dysfunction, coronary spasm, left ventricular (LV) hypertrophy, and serious dysrhythmias [30]. Moreover, 'wear and tear' from frequent allostatic loading, has been shown to trigger the onset or progression of mental health issues to which individuals are susceptible [31].

1.1 Research Aim

The name of our project is NUBI Drive, which stands for **N**aturalistic **UBI**quitous driving study. Using ubiquitous means, NUBI Drive investigates physiological arousal in apparently benign daily commutes. Millions of people drive daily for most of their lives. Next to computers and smartphones, cars are the machines people most frequently use. Much like there has been a significant interest in computer and smartphone use patterns that are physiologically unsettling, such as long screen times, we argue for an increased scrutiny on car use patterns that may do the same. For the latter, we do not refer to harmful but rare events, like crashes. We rather refer to insidious daily physiological activators, which people are not even consciously aware of. For instance, Huynh et al. showed that trivial acceleration events provoke hyperarousal responses in certain drivers [29]. The potential long-term effect of such repeated daily arousals is concerning. Accordingly, the key aim of our exploratory research is:

AIM: Identify physiologically unsettling car use patterns and measure their effects. The focus would be on cardiovascular activation, due to the nature of the available ubiquitous physiological sensors.

1.2 Contributions

Our NUBI Drive research makes the following important contributions in terms of insights, methods, and data:

1) It documents the association between anxiety predisposition and cardiovascular activation while driving. It also brings to the fore the association of higher speeds with higher heart rates. These insightful results stand to inform the management of driving patterns.
2) It operationalizes a ubiquitous computing methodology to efficiently carry out naturalistic driving studies with geographically dispersed participants. By unobtrusively capturing human, machine, and environmental variables, our method lives up to the multi-factorial challenges of such studies.
3) It facilitates research on physiologically unsettling effects of driving by making publicly available the data and code associated with this paper [https://github.com/UH-CPL/NUBI-DRIVE-1].

1.3 Comparison to Related Work

Among other state-of-the-art ubiquitous NDS, such as HARMONY [18], our study adds to the literature thanks to the following distinct characteristics:

Physiology vs. Safety. The focus of our research is not on safety issues but rather on insidious physiological effects of widespread driving patterns. This is a novel, potentially consequential, and understudied topic in driving studies.

More Ubiquitous vs. Less Ubiquitous. We operationalize ubiquitous NDS in a progressive way. While in other cases, researchers send to participants separate smartphones and smartwatches to use during the course of the study [18], we leverage the participants' own smartphones and smartwatches for data collection. This adds to the realism, naturalness, and scalability of our study.

Data Collection Targeting Behavioral Cycles. We view driving behaviors as human behaviors, embedded in a broader context and characterized by diurnal and weekly cycles [32]. For this reason, we collect data from participants for an entire week, not only during the times they drive, but also during the times they do not drive. We lock on a week as a monitoring period, because we consider it as standard cycle of human behavior. In other naturalistic driving studies, researchers do not collect non-driving data from participants; even their driving data are collected opportunistically, that is, driving data do not come from consecutive days of a specific week [22]

Analysis of Sustained vs. Event Based Behaviors. We do not focus on event-based behaviors (e.g., passing another vehicle), but rather on general behavioral patterns affected by weather conditions, traffic patterns, situational circumstances, and personal predispositions. This is a much needed complementary picture to specific instantaneous behaviors that have been the mainstay of NDS thus far [36]. Our focus also serves well our objective, which is to find insidious physiological effects of driving behaviors. Such effects are more likely to come from behaviors that have significant duration and frequency, such as daily commutes [37]; they are less likely to come from behaviors associated with rare and short-lived events, such as critical braking [38].

Ubiquitous, Multimodal, & Privacy-Preserving. Our design features broad multi-modality, encompassing physiological, machine, observational, traffic, weather, and psychometric data. This cornucopia of synchronized data channels brings together arousal, behavioral, situational, and dispositional information, facilitating disambiguation of confounding factors during analysis. Some variables, like traffic and weather signals, are absent in most NDS, thus denying important environmental context from their analysis. The only major data channel our study lacks is video data, but this is by design. The inclusion of video data renders a ubiquitous NDS, less ubiquitous, because most people do not have cameras installed in their cars. We also consider the video channel very intrusive and privacy-compromising, without bringing unique and essential information for our physiological outcomes study. In naturalistic driving studies, dual video, from cameras looking inside and outside, brings three pieces of information by the way of computer vision methods [18], [22]: a) drivers' apparent emotional valence through recognition of facial expressions; b) assessment of distractions (e.g., texting) through activity recognition; and, c) a measure of outside traffic through vehicle detection in the dash camera's field of view. We do not have access to

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TABLE 1: **Comparative list of naturalistic driving studies.** Characteristic study variables are grouped into four categories: a) General study attributes, such as data size; b) instantaneous car driving and environmental variables, such as traffic density expressed through Jam Factor; c) instantaneous human physiology and behavior variables, such as heart rate (HR) and hand motion; and d) dispositional and situational psychometric indicators, such as perceived loading from driving expressed via NASA-TLX.

	Study Variables	NUBI Drive	HARMONY [18]	100-Driver Study [23]	SHRP-2 [13]
General	**Study Aim**	Routine drive effects	Predict driver states	Driver distractions	Crashes
	Study Year	2022-23	2019-21	2021-22	2006-15
	Study Location	Texas	Virginia	China	Eastern US
	# Participants	21	21	100	3,247
	Dataset Size	76.70 driving hrs and 914.53 non-driving hrs	1 month driving	79.34 driving hrs	43,000 driving hrs
Environment – Car	**Car Speed**	✓	✓	–	✓
	Car Accel	✓	–	–	✓
	GPS	✓	✓	–	✓
	Jam Factor	✓	–	–	✓
	Weather	✓	✓	–	✓
Human Sensing	**Driving HR**	✓	✓	–	–
	Non-driving HR	✓	–	–	–
	Hand Accel	✓	✓	–	–
	Hand Gyro	✓	✓	–	–
	Computer Vision	–	✓	✓	–
Psychometrics	**Morning Anxiety** [33]	✓	–	–	–
	NASA-TLX [34]	✓	–	–	–
	Trait Anxiety [33]	✓	–	–	–
	Big-Five [35]	✓	–	–	–

the first, but we acquire the other two pieces of information with alternative means. In more detail, apparent emotional valence is difficult to capture without video, but is not very important for our physiological outcomes study. Basic distractions, that is, hands not on the wheel, are tracked in our case through the accelerometer and gyroscope in the drivers' smartwatch [39]. And, information about encountered traffic is captured through application programming interfaces (API), using the GPS coordinates from the drivers' smartwatch.

Table 1 shows a comparative summary of the characteristics of NUBI Drive against three other representative driving studies - HARMONY [18], 100-Driver Study [23], and SHRP-2 [13]. The size of NUBI Drive is similar to the size of HARMONY, which also features physiological information. By contrast, however, NUBI Drive features some additional variables that carry significant behavioral value. These variables include non-driving physiology and several psychometric indicators, such as the Big-Five personality traits [35]. The 100-Driver study represents a specialized effort focused on distractions. It features extensive computer vision information but little else. The SHRP-2 study has impressive size, but carries only car and environmental information; it lacks human sensing and psychometrics. Notably, the focus of SHRP-2 on crashes is in contradistinction to the focus of NUBI Drive on uneventful driving routines.

2 Study Design

We conducted a naturalistic driving study by recruiting drivers from the state of Texas in the United States. Texas was chosen as the recruiting ground because it boasts a renowned car culture [40], where nearly everybody drives on a daily basis. Furthermore, the state features a good mix of major metropolitan centers and rural areas, featuring a highly diverse population [41]. Recruitment was carried out through Facebook ads. The study procedures were approved by the Institutional Review Boards (IRB) of the participating institutions. We performed these procedures in accordance with the approved guidelines, obtaining informed consent from each participant. Prior to conducting the formal study, we extensively tested the protocol in pilot runs to identify and address any practical issues.

We collected biographic, psychometric, vehicle, observational, and environmental variables as predictive factors of

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sympathetic activation expressed by heart rate - the study's response variable. Factor selection was based on literature support, attesting to their influence on driving behaviors associated with sympathetic activation.

2.1 Participants

We monitored participants with no known health problems for one week. After consenting but before embarking on the study, the participants were trained in the relevant procedures. These procedures involved installing sensors, handling data collection apps, and sending the collected data to the project cloud. Following their training, the participants had to perform one test drive, to ensure everything goes smoothly, and we are receiving their data in good order. The monitoring period for all participants started on Monday mornings and ended on Sunday evenings. All communication between study administrators and participants took place via TEAMS.

Upon enrollment, the participants received via courier an on-board-diagnostics II (OBD2) device to record driving data during the study. They also received a $20 Amazon e-gift card as compensation for any expenses associated with the acquisition of the needed apps. Upon successful completion of the study, the participants received an additional $100 Amazon e-gift card and were free to keep the OBD2 device. The participants had to have an iPhone X or later model and an Apple Watch 5 or later model loaded with the latest versions of the iOS and watchOS, respectively. We did not allow drivers with Android phones and other types of smartwatches to enroll, to minimize the administrative burden associated with the management of a multi-platform study. In the case of the United States, where our study was conducted, this admission criterion did not materially bias our sample, as the great majority of U.S. residents have iPhones and Apple Watches (60% [42] and 91% [43] market share, respectively). Choosing the Apple ecosystem made also sense for interoperability reasons. The data acquisition in our study depended on smooth interoperability between the participant's smartwatch and smartphone, as data from the smartwatch moved to the smartphone before being transferred to the project's cloud.

The participants had to have a car, which they were driving daily. Regular commuters as well as people with more flexible schedules were welcome in the study, provided they were making substantial use of their cars. To qualify for enrollment, interested participants had to drive at least 20 miles per week. Participants also had to be healthy, have at least four years of driving experience, and be between 20 and 30 years old. The age criterion was put for two reasons: First, restricting the age range to young adults homogenized our sample from the physiological point of view [44], obviating the need for a large multi-group cohort. Second, because the study's main instruments were the participants' own ubiquitous devices, ease with these devices and their apps were crucial to the success of the project. In this regard, selecting young drivers for participants was a sound bet [45].

2.1.1 Participant Attrition and Data Loss

The main objective of this driving study was to analyze behavioral and physiological patterns during a typical week. As the observation horizon was a single week, there was little room for data loss within each participant. To be responsive to the study's objectives, the participants had to provide good data for at least four out of the five weekdays and at least one out of the two weekend days. This is more challenging than it sounds, given the whimsical nature of some of the technologies involved (especially, OBD2). We enrolled 34 participants, out of whom 21 produced usable data for analysis. We describe below the reasons for participant attrition and data loss:

1) Participants P10, P31, P43, and P51 quit the study after a couple of days and their data were struck from the record. This is not an uncommon occurrence in longitudinal studies [46].
2) Participants P11, P13, P26, P28, P34, and P41 completed the study but had a small and inadequate amount of data for the key variables of speed, throttle, and heart rate. This was due to bad luck or occasional inattentiveness, and thus of random rather than systematic nature. For instance, sometimes the OBD2 Bluetooth connection was not working and thus the speed and throttle values were lost for some trips. Or the participant's Apple watch was running out of battery and the heart rate recording from the app was lost before saved and transferred to the iPhone. If such mishaps were taking place over the weekend, compromising the weekend data, this participant could not be included in the set, because we knew nothing about his/her weekend behaviors – a fundamental objective of our study.
3) For participants P15, P17, and P19, all the values of the hand acceleration and gyroscope signals were missing. We traced the problem to incompatibility of these participants' Apple Watch 4 and the recording app; we made the possession of Apple Watch 5 or later model a hard requirement after these incidents. During model optimization (see section 3.2), these three participants could not partake in the selection of variables for which they suffered total data loss. Hence, they had to be dropped from the dataset, as no equitable optimization was possible in their presence.

2.2 Study Variables

NUBI Drive investigates physiological arousal in daily itineraries. Physiological arousal usually leads to stress, and we ask the question if seeds of stress are lurking in unsuspected routine activities. In affective computing, arousal is usually measured through one of the following physiological channels [47]: heart function, breathing function, or electrodermal activity (EDA). Because this study was ubiquitous by design, physiological signal collection depended on the drivers' own Apple Watches and no special wearable sensors were allowed. The Apple Watch and other popular smartwatches frequently measure heart function only; they infrequently measure breathing function, while they cannot measure EDA at all. Hence, we had little choice but to use heart function as a proxy of physiological arousal, since the other two options were either not available or severely limited. Ideally, in terms of heart function, we would need both heart rate and heart rate variability (HRV) for a solid fix on sympathetically driven physiological arousal. Here again, while Apple Watch measures heart rate every few seconds, it measures heart rate variability only a couple of times per day. This left us with heart rate - an index of cardiovascular activation - as the only viable physiological channel in our study.

Since driving entails physical inactivity, any cardiovascular activation while driving is likely to originate from sympathetic arousal or, possibly, from parasympathetic reduction. Accordingly, we included vehicular, environmental, observational, and psychometric variables (Table 2), which prior research links to sympathetic responses. These variables must account for a significant part of the drivers' sympathetic activation, which in turn, must explain a good part of the measured cardiovascular activation. We also included indicators of circadian rhythms, such as morning and afternoon periods, to account for cardiovascular activation due to parasympathetic reduction [48]. Aspects of sympathetic activation and parasympathetic reduction that are not unique to driving can be identified through complementary models, focused on the participants' non-driving life.

2.2.1 Environment - Car Variables

Car Signals. The participants were sent an OBD2 device to collect car signals during their drives. We chose BlueDriver [49], as it was the most highly rated OBD2 at the time of the study. The participants had to plug the BlueDriver device to the OBD2 port of their car. Every time they were driving during the monitoring period, the participants had to record their car signals through the BlueDriver OBD2 Scan Tool app. These recordings were sent to the project's server upon completion of each drive or shortly thereafter. The BlueDriver collects data for several car variables, but in this study we used only two: a) instantaneous speed in mph and b) throttle in degrees, taking values in the range $[0^\circ - 90^\circ]$; 0° corresponds to no throttle while 90° corresponds to full throttle. In well-maintained cars, throttle correlates with the car's acceleration. Speed and acceleration are the most fundamental perceptible effects the machine has on the driver, and because sympathetic activation works in concert with the senses [50], speed and throttle are integral to this investigation.

Geolocation (GPS) Signals. The participants were asked to record their geolocation during their drives - a piece of information necessary for obtaining matching traffic and weather information from open sources. GPS recording was effected via the SensorLog app, that is, the same app that was also used to acquire observational signals.

Environment Signals. There is support in the literature that traffic and weather conditions contribute significantly to driving stress [51], [52], and thus likely to cardiovascular activation. Accordingly, we used the GPS signals from the participants' drives to extract the corresponding traffic and weather conditions. To collect matching traffic data, we employed the ▲here application programming interface (API) [53]. The ▲here API provides traffic data for approximately every mile of road in US, updated every 10 minutes. One can extract several traffic related measures from the API's databank, but the key measure we used in this study is the Jam Factor. The Jam Factor takes values in the range $[0 - 10]$; values in the subrange $[0 - 4)$ indicate free flowing traffic; values in the subrange $[4 - 8)$ indicate sluggish flow of traffic; values in the subrange $[8 - 10)$ indicate slow flow of traffic; Jam Factor = 10 indicates that traffic stopped flowing or the road is closed. To collect matching weather data, we employed the OpenWeather API [54]. The OpenWeather API provides weather data for every GPS point, updated every 15 min. The reported information is a categorical variable featuring the following levels: {Thunderstorm, Drizzle, Rain, Snow, Haze, Smoke, Clear, Clouds}.

2.2.2 Human Sensing Variables

Physiological Signals. Heart rate served as a measure of drivers' cardiovascular activation, which for sitting subjects is often associated with sympathetic activation [55]. The participants were asked to record their heart rate via their Apple Watch throughout the day, that is, during both driving and non-driving periods. They used the HeartMonitor app [56] - a simple but robust app for long heart rate recording sessions. The app records heart rate values approximately every 5 seconds, which tends to drain the watch's battery. Accordingly, the participants were instructed to recharge their Apple Watch during lunch time, to last them until the end of the day.

Observational Signals. It was documented in other works that texting while driving is often habitual [57] and results into hyperarousal [58]; thus, it is of interest to the present study. Prior research showed that accelerometric and gyroscopic signal features from wrist-worn sensors can be used to detect distracted driving - mainly texting while driving [59]. When compared to computer vision [23], [24], [25], this is a less comprehensive method to quantify driving distractions, but a reasonable compromise in our case, where we use only ubiquitous car and wearable sensors. Accordingly, we asked participants to wear the Apple Watch on their 'texting hand', recording its tri-axle acceleration and gyroscope signals while driving. This recording was effected via the SensorLog app [60] at 36 Hz. We used signal energy - a fundamental signal feature - to operationalize detection of persistent distractions in a trip. Per standard practice in the literature [61], we consolidated the three-dimensional acceleration and gyroscope variables into two integrated energy measures - acceleration energy E_a and gyroscopic energy E_r:

$$\begin{aligned} E_a &= \frac{1}{T}\int_{t_0}^{t_0+T} (|a_x| + |a_y| + |a_z|)dt, \\ E_r &= \frac{1}{T}\int_{t_0}^{t_0+T} (|r_x| + |r_y| + |r_z|)dt, \end{aligned} \tag{1}$$

where a_x, a_y, and a_z are instantaneous accelerometer values, while r_x, r_y, and r_z are instantaneous gyroscope values corresponding to the x, y, and z axes; the interval of integration T was set to 1 s.

2.2.3 Psychometric Variables

In the course of their study involvement, participants had to complete trait psychometric questionnaires delivered once and state psychometric questionnaires delivered daily. All

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TABLE 2: **List of main variables used in NUBI Drive research.** The table includes the sampling frequency, the source, the value range, the relevance, and the mathematical symbols of the trip-level features associated with the variables.

	STUDY VARIABLES	Symbol	Relevance	Values	Source	Frequency
Environment – Car	**Car Speed**	$\overline{SP}$	Cardio loading from driving style	[0-100] mph	OBD2	1 Hz
	Car Accel	$\overline{TH}$	Cardio loading from driving style	[0-90]°	OBD2	1 Hz
	GPS		Insta-position to link context	Lat ∈ $[0, \pm 90°]$ / Lon ∈ $[0, \pm 180°]$	Apple Watch	36 Hz
	Jam Factor	$\overline{JF}$	Cardio loading from traffic	[0-10]	here API	minute level
	Weather	WE	Cardio loading from nature	[Good, Adverse]	OpenWeather API	minute level
Human Sensing	**Driving HR**	$\overline{DHR}$	Response variable	[40-160] BPM	Apple Watch	per 5 sec
	Non-driving HR	$\overline{NHR}$	Response variable	[40-200] BPM	Apple Watch	per 5 sec
	Hand Accel	$\overline{E}_a$	Cardio loading from distractions	$[0, \pm 2g]$	Apple Watch	36 Hz
	Hand Gyro	$\overline{E}_r$	Cardio loading from distractions	$[0, \pm 250°/\text{sec}]$	Apple Watch	36 Hz
Psychometrics	**Morning Anxiety** [33]	MA	Situational cardio loading	[20-80]	Qualtrics via iPhone	once a day
	NASA TLX [34]	TLX	Situational cardio loading	[1-7]	Qualtrics via iPhone	twice a day
	Trait Anxiety [33]	TA	Dispositional cardio loading	[20-80]	Qualtrics via iPhone	once
	Big-Five [35]	$B5$	Personality cardio loading	[2-10]	Qualtrics via iPhone	once

questionnaires were implemented in Qualtrics [62], and their links were texted to the participants' phones at the appropriate times. In more detail, participant monitoring was commencing on Mondays. The day before (i.e., Sunday), the participants had to complete three trait questionnaires: a biographic survey, the State and Trait Anxiety Inventory (STAI) Form Y-2 [33], and the Big Five Personality Test (Big-Five) [35].

Biographic Questionnaire. The biographic questionnaire inquired information about gender and age. Age was found to be an important predictor of sympathetic arousal during driving [58]. As our study recruited only young adults, our sample exhibited age homogeneity, and thus age information meant to play a confirmatory rather than modeling role. The gender information, however, meant to be included in the model, as prior research found women to be more likely to engage in self-regulation during driving [63], with all the implications this might have on sympathetic activation. The biographic questionnaire also inquired about the participants' driving experience, attitude towards driving, and commuting profile.

State and Trait Anxiety Inventory (STAI) Form Y-2. STAI Form Y-2 measures anxiety predisposition. Anxiety is intimately linked to sympathetic activation [64]. Moreover, drivers who have anxiety predisposition found to be more likely to engage in aberrant behaviors [65], [66], with all the implications this might have on sympathetic activation. STAI scores take values in the range [20, 80], with higher scores indicating greater anxiety [33]. Scores greater than 40 indicate anxious individuals [67].

Big Five Inventory (Big-Five). Big-Five is related to the participants' key personality traits [35]. Big-Five was found to predict aggressive and risky driving [68], behaviors typically associated with sympathetic activation. In the present study, we used the short 10-item version of Big-Five featuring the following sub-scales: [69].

- Agreeableness $-$ $B5A$: The level of participant's friendliness with score range [2–10].
- Conscientiousness $-$ $B5C$: The level of participant's organized nature with score range [2–10].
- Extraversion $-$ $B5E$: The level of participant's outgoing nature with score range [2–10].
- Neuroticism $-$ $B5N$: The level of participant's nervousness with score range [2–10].
- Openness $-$ $B5O$: The level of participant's curiosity with score range [2–10].

State and Trait Anxiety Inventory (STAI) Form Y-1. Each day of the monitoring period, the participants had to complete in the morning the STAI Form Y-1 questionnaire [33], measuring their level of anxiety at the start of the day. Morning anxiety, owing to anticipation of stressful events later in the day, was shown to affect working memory [70], which plays an important role on hazard perception in driving [71], with obvious implications to sympathetic activation. For this reason, we decided to consider a measure of morning anxiety in our modeling.

NASA Task Load Index (NASA-TLX). NASA-TLX is a multidimensional assessment tool that rates perceived workload [34]. In our study, it meant to measure the perceived driving workload. It has been documented in the literature that NASA-TLX scores correlate with arousal levels during driving [58]. Hence, they can be used to rank the arousing nature of the drives under investigation, affirming also the corresponding physiological results. As our design considers two phases in the day cycle - morning and afternoon, the participants had to complete each day two NASA-TLX questionnaires, respectively. The first NASA-TLX meant to assess the loading incurred by the participants' morning trips. It was delivered to the participants' phones at noon, and they had to complete it shortly thereafter. The second NASA-TLX meant to assess the loading incurred by the

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participants' afternoon trips. It was delivered to the participants' phones at 6:30 pm, and they had to complete it shortly thereafter or when they returned home. NASA TLX features six sub-scales with common rating [1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree]:

- Mental Demand $- \; TLX_{MD}$: Perceived mental load induced by morning|afternoon drive(s).
- Physical Demand $- \; TLX_{PD}$: Perceived physical activity induced by morning|afternoon drive(s).
- Temporal Demand $- \; TLX_{TD}$: Perceived time pressure induced by morning|afternoon drive(s).
- Performance $- \; TLX_{P}$: Perceived success in executing morning|afternoon drive(s).
- Effort $- \; TLX_{E}$: Perceived amount of work expended to achieve said performance in morning|afternoon drive(s).
- Frustration $- \; TLX_{F}$: Perceived level of irritation in performing morning|afternoon drive(s).

Conventionally, NASA-TLX is applied to single tasks and thus should have been administered after every drive. In pilot trials, however, we found that this was logistically difficult, as it was interfering with the integrity of sensor data acquisition, and it was fast expending the good will of participants. Per the study protocol, when participants were arriving at their destination, they had to spend a few minutes prior to exiting the car to close the relevant recording apps and beam the data to the cloud. Filling out a questionnaire atop of all these was too much for some pilot volunteers, as they were typically under time pressure. In their haste to do everything, they were often compromising the handling of the sensor data. Sometimes they also had to drive to another place shortly thereafter for a special meeting or other occasion, which made the whole process even more onerous. Thankfully, recent research has documented that NASA-TLX can be applied not only to single tasks but also to task sequences without loss of validity [72]. Accordingly, and taking advantage of the natural divide offered by the lunch break, we opted to apply one NASA-TLX for all morning trips and one for all afternoon/evening trips, something that dovetailed with our behavioral pattern design. The concordance of the NASA-TLX scores with the physiological measurements (see section 3.5), confirmed the soundness of our design.

3 Results

3.1 Descriptive Statistics

The $n_P = 21$ study participants resided in 15 different cities across the state of Texas (Fig. 1) and undertook a total of $n_T = 256$ trips during the monitoring period. From these trips, 200 took place in weekdays and 56 in weekends. The weekday trip duration was 18.7 ± 14.1 min, while the weekend trip duration was 15.2 ± 9.6 min. Summing up all trips, the total driving time in the dataset amounts to 76.7 hours. The dataset also includes 914.53 hours of non-driving data. Altogether the momentary driving and non-driving data constitute 3,703,774 rows of multimodal information. Trip level analysis in all subsequent modeling was applied

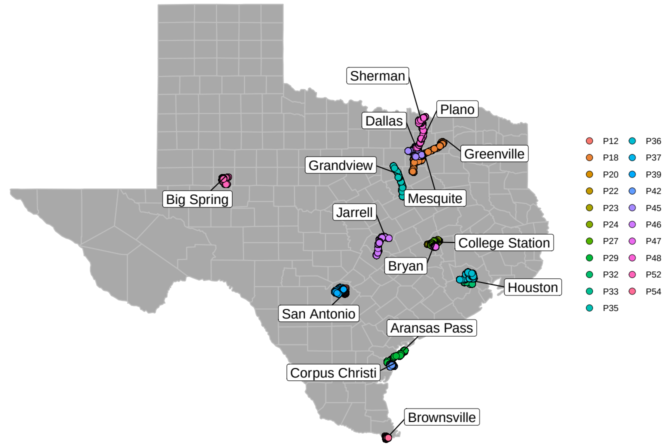

Fig. 1: **Itineraries of participants in the NUBI-1 dataset.** The sample includes a mix of major metropolitan areas, like Houston and smaller cities, like Bryan.

to this dataset, which we will refer to as NUBI-1 - short for *Naturalistic UBIquitous* driving study dataset 1.

NUBI-1 consists of 14 males and 7 females. By design, the study was restricted to young adults, which is reflected in the sample's age statistics: 27.5 ± 6.8 years of age. All participants acquired their driving license when 16, and were driving ever since. Given that the mean age of the sample was 27.5, the typical participant had over 10 years of driving experience. Furthermore, 90.5% of participants had a regular commuting schedule, while 66.7% of participants drove well over 50 miles per week; no participant drove less than 20 miles per week.

Figure 2 shows descriptive plots of key NUBI-1 variables at the trip level, reflecting the values used in our modeling process. In more detail, Fig. 2a shows the physiological, vehicular, and observational variable box-plots. The distribution of mean trip heart rates (86.5 ± 10.3 BPM) features a good range; it extends all the way down to values typically associated with relaxed states ($< \sim 70$ BPM) [73], and all the way up to values typically associated with hyperaroused states ($> \sim 90$ BPM) [74] for healthy sitting subjects. The distribution of mean trip speeds (26.2 ± 12.7 mph) is centered on values indicative of city street itineraries ($\sim$ 30 mph), but extends all the way to values indicative of highway itineraries ($\sim$ 60 mph). The distribution of accelerometer energy (1.3 ± 0.4) stands higher than the distribution of gyroscopic energy (0.7 ± 0.4), reflecting the limited rotational patterns associated with typical driving and texting.

Figure 2b shows descriptive plots of the environmental variables. The distribution of mean trip Jam Factors (1.4 ± 0.8) does not exceed 4, which indicates that the overall traffic flow in the dataset's trips was relatively unhindered. The weather bar-plots indicate that the prevailing weather in the great majority of trips was either fair (26.6%) or cloudy (68.8%), thus posing no driving problems.

Figure 2c shows descriptive plots of the NUBI-1 participants' state psychometrics. The participants had a near Normal morning anxiety distribution (32.1 ± 10.1) with its mean 32.1 near the center of the non-pathological subrange [20, 40]. The NASA-TLX distributions for the subscales

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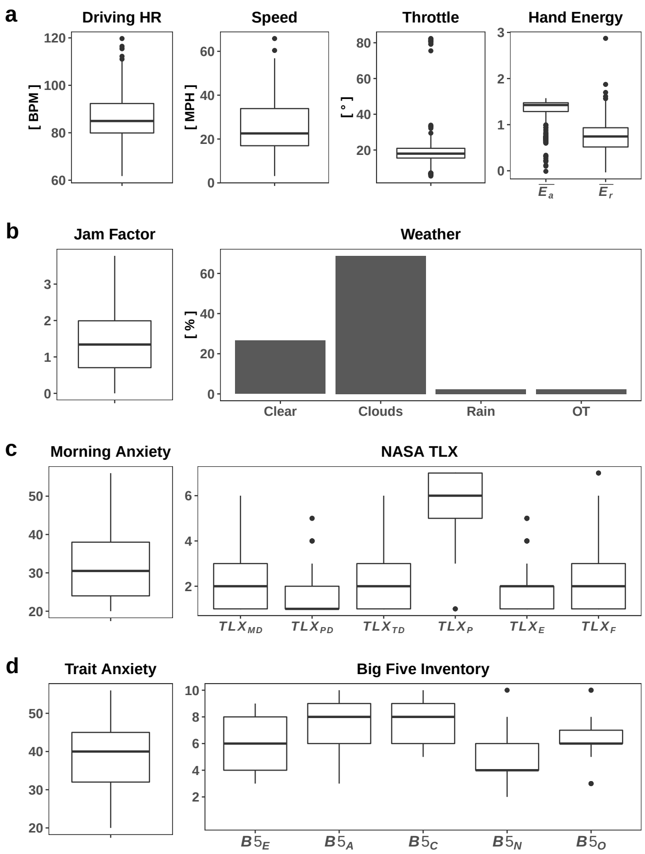

Fig. 2: **Descriptive plots of key modeling variables. a.** Box-plots of mean trip values for driving heart rate $\overline{DHR}$, speed $\overline{SP}$, throttle $\overline{TH}$, hand acceleration energy $\overline{E}_a$, and hand gyroscopic energy $\overline{E}_r$. **b.** Box-plot of mean trip Jam Factor $\overline{JF}$ and bar-plots of prevailing weather pattern per trip, where Rain consolidates rain, thunderstorm, and drizzle categories, while OT consolidates haze and smoke categories. The Jam Factor distribution suggests relatively unhindered traffic flow in the dataset's trips, while the weather plots indicate perfect driving weather in the great majority of cases. **c.** Box-plots of participants' morning anxiety MA and NASA-TLX scores TLX_{MD}, TLX_{PD}, TLX_{TD}, TLX_P, TLX_E, and TLX_F for perceived Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration, respectively. The high scores of the Performance subscale TLX_P stand out, indicating the largely uneventful character of the dataset's trips. **d.** Box-plots of participants' trait anxiety TA and Big-Five subscales $B5_E$, $B5_A$, $B5_C$, $B5_N$, and $B5_O$ for Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness, respectively. Participants exhibit good ranges across all variables, suggesting healthy phenotypical diversity.

Mental Demand (1.9 ± 1.1), Physical Demand (1.6 ± 0.8), Temporal Demand (2.1 ± 1.3), Effort (1.9 ± 1.0), and Frustration (2.1 ± 1.4) feature low to moderate values. The NASA-TLX distribution for Performance (5.5 ± 1.3), is the only one that features high values, indicating the satisfaction of the drivers with the trip execution. This reflects the largely uneventful character of these trips, where no crashes and tickets were recorded.

Figure 2d shows descriptive plots of the NUBI-1 participants' phenotypical characteristics. The participants had a nearly Normal trait anxiety distribution (39.2 ± 9.5), with its mean 39.2 being on the high end of the non-pathological subrange [20, 40]. The agreeableness and conscientiousness distributions of the participants were centered on the high end of the Big-Five range with 7.3 ± 1.9 and 7.6 ± 1.4, respectively. The participants' extraversion and openness distributions were centered just above the middle of the Big-Five range with 6.0 ± 2.1 and 6.3 ± 1.9, respectively. Finally, the participants' neuroticism distribution was centered near the middle of the Big-Five range with 5.0 ± 1.9.

While Fig. 2 shows the mean trip statistics upon which subsequent models operate, Fig. 3 gives a glimpse of the underlying instantaneous data for participant P27. The participant is a typical commuter, as can be seen from the clustering of his trip signals. His morning commute takes place just before 7:00 o'clock, while his afternoon commute just before 17:00 o'clock. Occasionally, the participant ventures out between 11:00 and 13:00 o'clock for his lunch break. He ventures out late in the evening only on Friday, likely for a night out. In his daily trips, the participant is blessed with good driving weather (clear or overcast). He encounters rain in just one occasion. There is unhindered traffic flow in the great majority of the participant's driving (Jam Factor < 4). He briefly encounters serious traffic only towards the end of his morning commute (Jam Factor between 4 and 8).

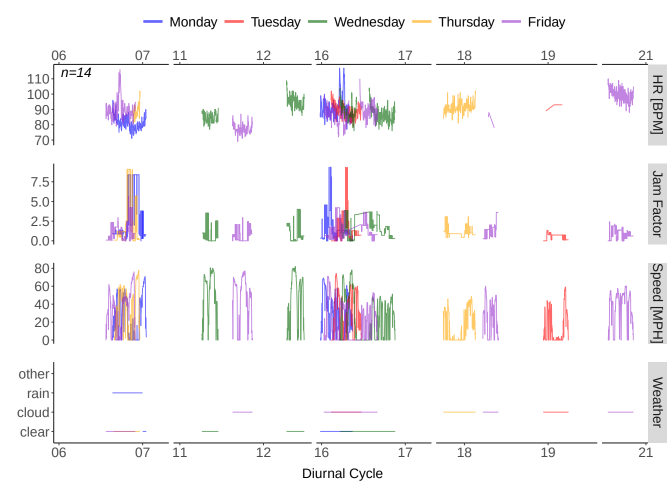

Fig. 3: **Weekday signals of key model variables for participant P27.** Trips ($n = 14$) from different weekdays are represented by different colors. The signals visualize the instantaneous values of HR, Speed, Jam Factor, and Weather during the trips. Out of these instantaneous values, the mean/mode trip statistics are computed, which are used in the plots of Fig. 2 and the models.

3.2 Driving Heart Rate Model

We first report on the predictors of participants' driving heart rate. For that, we construct a multiple linear regression model, where the response variable is $\overline{DHR}(i,j,k,l)$, that is, participant's P_i mean heart rate in trip k of day j, with the trip having taken place in l = Morning or Afternoon. The predictors include participant's P_i traits, state psychometrics, driving behaviors, and environmental context. The full model is in Eq. (2).

$$\begin{aligned}
\overline{DHR}(i,j,k,l) \sim\ & \beta_0 + \beta_1 GEN(i) + \\
& \beta_2 TA(i) + \beta_3 B5A(i) + \beta_4 B5C(i) + \\
& \beta_5 B5E(i) + \beta_6 B5N(i) + \beta_7 B5O(i) + \\
& \beta_8 MA(i,j) + \beta_9 TLX(i,j,l) + \\
& \beta_{10} DI(i,j) + \beta_{11} PI(i,j,l) + \\
& \beta_{12} \overline{SP}(i,j,k) + \beta_{13} \overline{TH}(i,j,k) + \\
& \beta_{14} \overline{E}_a(i,j,k) + \beta_{15} \overline{E}_r(i,j,k) + \\
& \beta_{16} \overline{JF}(i,j,k) + \beta_{17} \mathrm{Mo}(WE)(i,j,k) + 1|S.
\end{aligned} \tag{2}$$

The first three lines of Eq. (2) - underlined in blue - hold the participant's biographic and trait psychometric predictors. Specifically, $GEN(i)$ stands for the gender of participant P_i, taking one of two values: Male or Female. $TA(i)$ stands for the STAI Form Y-2 score of participant P_i. $B5A(i), B5C(i), B5E(i), B5N(i)$ and $B5O(i)$ stand for the agreeableness, conscientiousness, extraversion, neuroticism, and openness scores of participant P_i.

The next two lines of Eq. (2) - underlined in cyan - hold the participant's subjective assessments, as well as the trip's temporal context. In more detail, $MA(i,j)$ stands for the STAI Form Y-1 score of participant P_i, indicating his/her level of morning anxiety in day j. $TLX(i,j,l)$ stands for the total NASA-TLX score of participant P_i in day j, expressing his/her perceived loading due to driving in period l (Morning or Afternoon). $DI(i,j) \equiv j$ is the day indicator. $PI(i,j,l) \equiv l$ is the period of day indicator (Morning or Afternoon), in day j, of participant P_i.

The next two lines of Eq. (2) - underlined in red - hold the participant's driving behaviors in the form of vehicular and observational predictors. Specifically, $\overline{SP}(i,j,k)$ is the mean speed of participant P_i in trip k of day j. $\overline{TH}(i,j,k)$ is the mean absolute throttle position of participant P_i in trip k of day j. $\overline{E}_a(i,j,k)$ and $\overline{E}_r(i,j,k)$ are the mean acceleration and gyroscopic energy, respectively, of participant's P_i 'texting' hand while driving in trip k of day j.

The last line of Eq. (2) holds the environmental predictors. In more detail, $\overline{JF}(i,j,k)$ stands for the mean jam factor participant P_i encountered in trip k of day j. $\mathrm{Mo}(WE)(i,j,k)$ stands for the mode of the weather pattern that participant P_i encountered during trip k of day j. The term $1|S$ indicates that we take into account participant-centered random effects. Accounting of random effects considers, among other things, the inter-individual variability of heart rate. This is important, because we do not know the baseline heart rate of participants to perform direct normalization. We are further protected in this respect by the similar young age of all participants, as age is an important contributor to differences in baseline heart rate.

Prior to solving the model, we construct the cross-correlation matrix for all variables listed in Eq. (2) to check for collinearities - Fig. 4. Some correlations rise above others. As expected, mean trip speed $\overline{SP}$ correlates with mean trip throttle $\overline{TH}$ ($r = 0.4$), while trait anxiety TA correlates with morning anxiety MA ($r = 0.6$). No correlation, however, is stronger than $r = \pm 0.6$. Due to the absence of excessive cross-correlations, no variable removal in the model is necessary. Subsequently, we run the following model optimization process, based on the Akaike information criterion (AIC), which unlike p-value optimization provides protection from Type I errors:

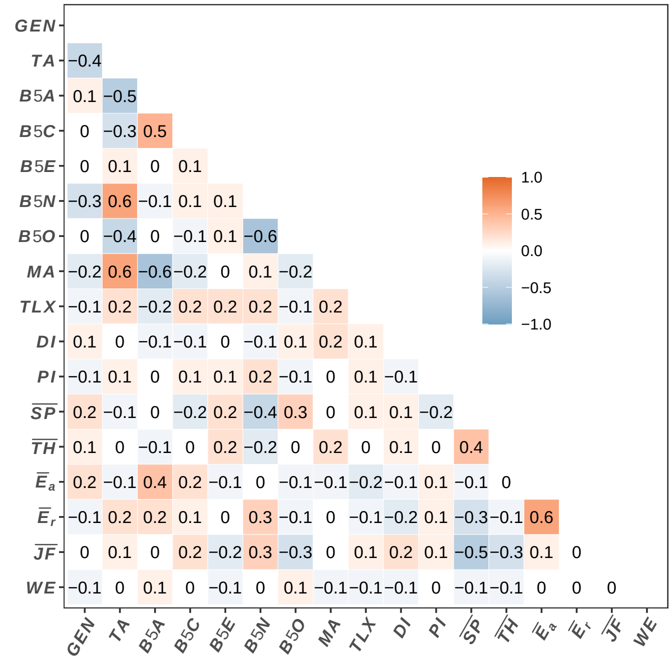

Fig. 4: **Cross-correlation matrix of all predictors in Eq. (2).** There are some significant correlations, such as between mean trip speed $\overline{SP}$ and throttle $\overline{TH}$, which are to be expected. No correlation coefficient in the table, however, exceeds ± 0.6.

STEP 1 Starting from the full model in Eq. (2), we sculpt a leaner model through backward elimination:

$$\begin{aligned}
\overline{DHR}_B(i,j,k,l) \sim\ & \beta_{B0} + \beta_{B1} GEN(i) + \\
& \beta_{B2} TA(i) + \beta_{B3} B5C(i) + \\
& \beta_{B4} DI(i,j) + \beta_{B5} PI(i,j,l) + \\
& \beta_{B6} \overline{SP}(i,j,k) + 1|S.
\end{aligned} \tag{3}$$

STEP 2 Starting from an empty model, we build an optimal model through forward selection of the best variables included in Eq. (2), until the model no longer improves:

$$\begin{aligned}
\overline{DHR}_F(i,j,k,l) \sim\ & \beta_{F0} + \beta_{F1} GEN(i) + \\
& \beta_{F2} TA(i) + \beta_{F3} B5C(i) + \\
& \beta_{F4} B5N(i) + \beta_{F5} B5O(i) + \\
& \beta_{F6} DI(i,j) + \beta_{F7} PI(i,j,l) + \\
& \beta_{F8} \overline{SP}(i,j,k) + 1|S.
\end{aligned} \tag{4}$$

STEP 3 Starting with the forward model in Eq. (4), which is a superset of the backward model in

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Eq. (3), we manually add and remove items (like interactions), just in case the automated methods missed something. At the end, we remove insignificant terms that do not materially affect the AIC, arriving at the optimized model of Eq. (5). The AIC of the optimized model in Eq. (5) is 1806.3 - a significant improvement from 1839.6 of the full model in Eq. (2).

$$\overline{DHR}'(i,j,k,l) \sim \beta_0' + \beta_1' GEN(i) + \beta_2' TA(i) + \beta_3' B5C(i) + \beta_4' DI(i,j) + \beta_5' PI(i,j,l) + \beta_6' \overline{SP}(i,j,k) + 1|S. \tag{5}$$

Table 3 provides a comprehensive list of the optimized driving model's parameter estimates, while Fig. 5 shows the plots of the model's results. The results suggest that gender, trait anxiety, conscientiousness, weekly/diurnal cycles, and speed are significant predictors of heart rate while driving. To give a clear idea of the factor effects, we report comparative results with respect to the model's Baseline Driver (BD) - a useful yardstick. This baseline driver does not exist in the dataset as such. It is a model construct that is defined by the baseline levels of categorical predictors and the mean values of quantitative predictors in Eq. (5). Accordingly, BD is conceptualized as female, with TA score 39.23, conscientiousness score 7.77, who drives in the morning of weekdays, and at an average speed of 26.24 mph; conveniently, the latter happens to be typical city street speed. Substituting these values in Eq. (5), we find that BD has a mean driving heart rate of $\overline{DHR}_{\text{BD}} = 38.037 + 0.471 \times 39.23 + 2.438 \times 7.77 + 0.114 \times 26.23 = 78.5$ bpm.

Keeping this context in mind, and varying only one factor at a time, while keeping all other factors constant, the coefficients in Table 3 suggest the following: Male drivers exceed the heart rate of BD by about 10 bpm. For every 10 points above the TA score of BD, drivers' heart rate is loaded with additional $10 \times 0.471 \approx 5$ bpm. For every point above the conscientiousness score of BD, drivers' heart rate is loaded with additional ~ 2.5 bpm. Drivers who drive in the weekends have lower heart rate with respect to BD by about 3 bpm. Drivers who drive in the afternoons exceed the heart rate of BD by about 4.5 bpm. Finally, for every 10 mph of additional speed, drivers' heart rate is loaded with additional $10 \times 0.114 \approx 1$ bpm. Hence, at the typical highway speed of 65 mph, which is about 40 mph higher than the speed of BD, the heart rate premium is 4 bpm.

The time complexity of a multi-regression model - such as the one we use here - is $O(p^2 n + p^3)$, where n is the number of data rows and p is the number of features [75]. Consequently, as far as the number of features is relatively small, the complexity of the model is near linear to the number of data rows. In our case, the maximum number of predictive features is 17 - see the full model in Eq. (2). This is a reasonable size feature set, and our model runs instantly on a typical MacBook Pro with 32 GB of memory.

3.3 Non-driving Heart Rate Model

To examine if the effects of participants' traits and morning anxiety are unique to driving heart rate (see Eq. (2)) or also extend into their non-driving heart rate, we construct the multiple linear regression model shown in Eq. (6).

$$\overline{NHR}(i,j) \sim \gamma_1 GEN(i) + \gamma_2 TA(i) + \gamma_3 B5A(i) + \gamma_4 B5C(i) + \gamma_5 B5E(i) + \gamma_6 B5N(i) + \gamma_7 B5O(i) + \gamma_7 B5O(i) + \gamma_8 MA(i,j) + 1|S. \tag{6}$$

The response variable is $\overline{NHR}(i,j)$, that is, participant's P_i mean non-driving heart rate in day j. The predictors include all the biographic and trait psychometric factors plus the morning anxiety assessments we encountered in

TABLE 3: **Results of the optimized mixed effects driving model described by Eq. (5).** β' stands for the coefficient estimates, SE for Standard Error, and df for degrees of freedom. The baselines of the categorical variables gender GEN, day indicator DI, and period of day indicator PI are Female, Weekday, and Morning, respectively. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Predictor	β'	SE	df	t value	Pr(> $\|t\|$)	
Intercept	38.037	9.737	16.227	3.907	0.001	**
GEN[Male]	9.701	2.574	14.392	3.769	0.002	**
TA	0.471	0.129	13.971	3.660	0.003	**
$B5C$	2.438	0.806	14.509	3.024	0.009	**
DI[Weekend]	−2.689	1.228	241.485	−2.190	0.029	*
PI[Afternoon]	4.549	1.048	238.266	4.341	<0.001	***
$\overline{SP}$	0.114	0.050	210.632	2.299	0.023	*

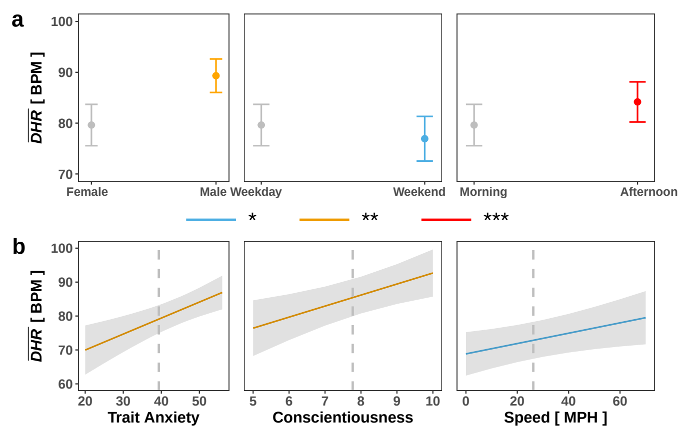

Fig. 5: **Main effects of the optimized mixed-effects driving model expressed in Eq. (5). a.** Categorical associations of demographic and temporal predictors with mean driving heart rate $\overline{DHR}$. Gray error bars are related to the predictors' baseline levels. Color error bars suggest significant differences from the respective baseline levels, as the figure's legend in the middle indicates. **b.** Quantitative associations of psychometric predictors and driving behaviors with mean driving heart rate $\overline{DHR}$. Hyphenated lines mark the mean values of the corresponding predictors. Color curves suggest significant associations, as the figure's legend in the middle indicates. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

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the full driving model expressed in Eq. (2). Specifically, $GEN(i)$ stands for the gender of participant P_i. $TA(i)$ stands for the STAI Form Y-2 score of participant P_i. $B5A(i), B5C(i), B5E(i), B5N(i)$ and $B5O(i)$ stand for the agreeableness, conscientiousness, extraversion, neuroticism, and openness scores of participant P_i. $MA(i, j)$ stands for the STAI Form Y-1 score of participant P_i, indicating his/her morning anxiety in day j.

TABLE 4: **Results of the mixed effects non-driving model described by Eq. (6).** $\gamma\cdot$ stands for the coefficient estimates, SE for Standard Error, and df for degrees of freedom. The baseline of the categorical variable gender GEN is Female. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Predictor	$\gamma\cdot$	**SE**	**df**	t **value**	**Pr(**$> \|t\|$**)**
Intercept	28.254	21.482	12.239	1.315	0.213
GEN[Male]	14.449	3.591	11.631	4.023	0.002 **
TA	0.475	0.276	12.517	1.722	0.110
$B5A$	−0.071	1.038	12.113	−0.068	0.947
$B5C$	2.855	1.136	11.933	2.513	0.027 *
$B5E$	−0.381	0.739	11.199	−0.516	0.616
$B5N$	0.220	1.235	12.546	0.178	0.861
$B5O$	1.284	1.068	12.737	1.202	0.251
MA	0.091	0.084	161.382	1.084	0.280

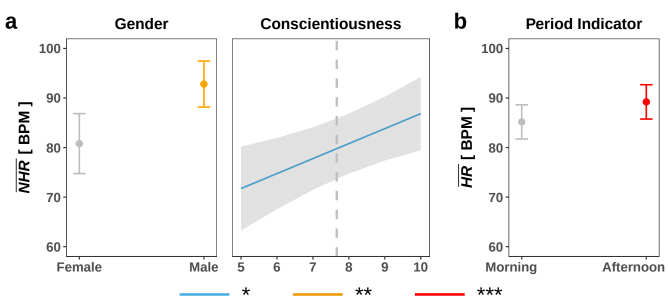

Fig. 6: **Significant main effects of the mixed-effects models expressed in Eqs. (6) & (7). a.** Associations of gender and conscientiousness with mean non-driving heart rate $\overline{NHR}$. **b.** Association of period of day with general mean heart rate $\overline{HR}$. Gray error bars in the categorical predictors gender and period of day are related to the corresponding baseline levels. The hyphenated line marks the mean value of the quantitative predictor conscientiousness. Per the figure's legend, color error bars suggest significant differences from the respective baseline levels and color curves suggest significant associations. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 4 provides a comprehensive list of the non-driving model's parameter estimates, while Fig. 6a shows the plots of the model's significant results. The results suggest that gender and conscientiousness are significant predictors of non-driving heart rate. To give a clear idea of the factor effects, we report comparative results with respect to the Baseline Non-driving Participant (BND). This baseline non-driving participant is again a conceptual yardstick, defined by the baseline levels of categorical predictors and the mean values of quantitative predictors in Eq. (6). Accordingly, BND is conceptualized as female, with TA score 39.23, agreeableness score 7.41, conscientiousness score 7.63, extraversion score 5.89, neuroticism score 5.09, openness score 6.24, and morning anxiety score 32.17. Substituting these values in Eq. (6), we find that BND has a mean non-driving heart rate of $\overline{NHR}_{\text{BND}} = 28.254 + 0.475 \times 39.23 - 0.071 \times 7.41 + 2.855 \times 7.63 - 0.381 \times 5.89 + 0.22 \times 5.1 + 1.284 \times 6.24 + 0.091 \times 32.17 = 78.0$ bpm.

Keeping this context in mind, and varying only one factor at a time, while keeping all other factors constant, the coefficients in Table 4 suggest the following: Male participants when do not drive exceed the heart rate of BND by about 14.5 bpm. For every point above the conscientiousness score of BND, participants' non-driving heart rate is loaded with additional ~ 3 bpm. Comparing these results with the results of the driving model in Table 3, we observe that gender and conscientiousness have associations of nearly the same order with both driving and non-driving heart rate. Trait anxiety, however, is significantly associated only with driving heart rate.

3.4 Nondescript Model - Association of Temporal Context With Driving and Non-driving Heart Rate

To examine whether temporal context affects the heart rate of participants not only when they drive but also in non-driving activities, we construct the multiple linear regression model shown in Eq. (7).

$$\begin{aligned}\overline{HR}(i,j) \sim &\zeta_1 ACT(i,j) + \zeta_2 DI(i,j) + \zeta_3 PI(i,j,l) + \\ &\zeta_4 ACT(i,j) \times DI(i,j) + \\ &\zeta_5 ACT(i,j) \times PI(i,j,l) + 1|S.\end{aligned} \tag{7}$$

The response variable is $\overline{HR}(i,j)$, that is, participant's P_i mean heart rate in day j. The predictors include the type of activity that produces $\overline{HR}(i,j)$, the associated temporal context, and interactions thereof. Specifically, $ACT(i,j)$ stands for the activity of participant P_i in day j, be that a Driving activity (i.e., trip) or a Non-driving one. $DI(i,j)$ is the day indicator, which maps to two values: Weekday and Weekend. $PI(i,j,l)$ is the period of day indicator, which maps to two values: l = Morning or Afternoon.

Table 5 provides a comprehensive list of the nondescript model's parameter estimates, while Fig. 6b shows the plot of the model's significant result. The result suggests that people have significantly higher heart rate in the afternoon relative to the morning. As the insignificant interactions indicate, this is a general result, irrespective of the activity the participants are engaged in, be that driving or non-driving. Altogether this result and the results from the driving and non-driving models in Tables 3 and 4, respectively, lead to the conclusion that only propensity for anxiety and driving speed bear unique associations to driving heart rate. Gender, conscientiousness, and temporal context associate with heart rate across driving and non-driving activities.

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TABLE 5: **Results of the mixed effects nondescript model described by Eq. (7).** $\zeta\cdot$ stands for the coefficient estimates, SE for Standard Error, and df for degrees of freedom. The baselines of the categorical variables activity ACT, day indicator DI, and period of day indicator PI are Non-Driving, Weekday, and Morning. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Predictor	$\zeta\cdot$	SE	df	t value	Pr(> $\|t\|$)	
Intercept	85.396	1.850	28.027	46.169	<0.001	***
ACT[Driving]	−1.122	1.161	330.001	−0.967	0.334	
DI[Weekend]	−0.914	1.510	334.227	−0.606	0.545	
PI[Afternoon]	4.508	1.112	330.729	4.054	<0.001	***
ACT[Driving] × DI[Weekend]	−0.826	1.984	330.185	−0.417	0.677	
ACT[Driving] × PI[Afternoon]	0.657	1.543	330.115	0.425	0.671	

3.5 NASA-TLX Model - Linking Drivers' Subjective Perspectives w/ Physiological Processes

The driving model expressed in Eq. (5) indicates that the heart rate of drivers is significantly higher in the afternoons vs. mornings and in the weekdays vs. weekends. This cardiovascular activation may be partly due to increased sympathetic activity and partly due to decreased parasympathetic activity. To shed more light into the phenomenon, we perform temporal analysis of the participants' perceived driving workload. Accordingly, we construct the multiple regression model shown in Eq. (8).

$$TLX_s(i,j,l) \sim \lambda_0 + \lambda_1 DI(i,j) + \lambda_2 PI(i,j,l) + \lambda_3 DI(i,j) \times PI(i,j,l) + 1|S. \quad (8)$$

The response variable is $TLX_s(i,j,l)$, which stands for the NASA-TLX subscale score s, of participant i, for the driving he/she performed during period l (morning or afternoon) of day j. On the predictor side of Eq (8), we use the two temporal predictors we have been using throughout this study, and their interaction. These are: the day indicator $DI(i,j) \in \{\text{Weekday}, \text{Weekend}\}$, and the period of day indicator $PI(i,j,l) \in \{\text{Morning}, \text{Afternoon}\}$.

Participants submitted scores for all six subscales of NASA-TLX, that is, $s \in \{MD, PD, TD, P, E, F\}$, twice per day. In doing so, they quantified their perceptions about how mentally (MD) and physically (PD) demanding the drives were during the morning or afternoon period. They also expressed the time pressure (TD) they felt while driving during that period. Finally, participants estimated the quality of their driving (P), how much effort (E) they put to achieve this level of performance, and their level of frustration (F) during the said driving.

In all, we run six versions of Eq. (8), one for each NASA-TLX subscale. The versions corresponding to the temporal demand (TD) and effort subscale (E) give significant results; the rest, do not. In more detail, Table 6a shows the results for the TLX_{TD} version of Eq. (8), while Fig. 7a shows the associated plot. Table 6b shows the results for the TLX_E version of Eq. (8), while Fig. 7b shows the associated plots. It is clear that participants feel significantly more time pressure during their weekday drives with respect to their weekend drives. The nature of this feeling points to likely sympathetic activation [76]. It is also clear that participants feel they expend significantly more effort to carry out their afternoon drives with respect to their morning drives. The context of this feeling points to likely parasympathetic reduction, linked to circadian rhythm [48]. The two results provide insights into the likely underlying processes that contribute to higher driving heart rates in the weekdays and afternoons, correspondingly.

TABLE 6: **Significant results for the family of mixed effects models expressed by Eq. (8). (a)** Model estimates when the response variable is TLX_{TD}. **(b)** Model estimates when the response variable is TLX_E. The baselines of the categorical variables day indicator DI, and period of day indicator PI are Weekday, and Morning. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

(a) TLX_{TD}

Predictor	$\lambda\cdot$	SE	df	t value	Pr(> $\|t\|$)	
Intercept	2.221	0.177	232	12.571	<0.001	***
DI[Weekend]	−0.887	0.361	232	−2.454	0.015	*
PI[Afternoon]	−0.126	0.179	232	−0.703	0.483	
DI[Weekend] × PI[Afternoon]	0.557	0.419	232	1.330	0.185	

(b) TLX_E

Predictor	$\lambda\cdot$	SE	df	t value	Pr(> $\|t\|$)	
Intercept	1.809	0.168	232	10.748	<0.001	***
DI[Weekend]	0.291	0.218	232	1.336	0.183	
PI[Afternoon]	0.298	0.107	232	2.777	0.006	**
DI[Weekend] × PI[Afternoon]	−0.586	0.251	232	−2.333	0.021	*

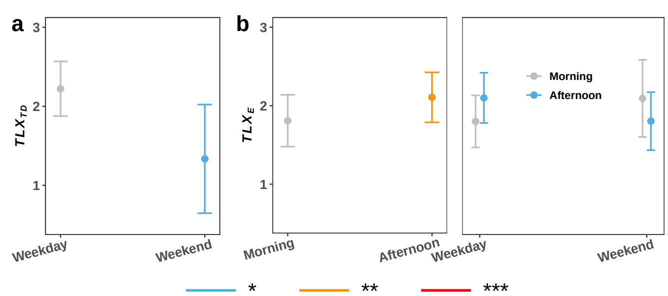

Fig. 7: **Significant main effects and interactions of the NASA-TLX model expressed by Eq. (8) a.** Association of day indicator with perceived time pressure TLX_{TD} during driving. **b.** Association of period of day indicator with perceived driving effort TLX_E, as well as interaction effects. Gray error bars are associated with the baseline levels Weekday and Morning. Color error bars indicate significant effects per the figure's legend. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

4 Discussion

Although long-term effects of daily driving might be concerning, it is difficult to be aware of the problem in the first place. This is because short-term effects of daily driving are not immediately obvious, due to their moderate impact and the existence of confounding factors [29]. Even when suspicions arise, it is not easy to measure and validate short-term effects of daily driving, because that involves continuous and unobtrusive monitoring of people. The latter is associated with challenges in the design, execution, and analysis of naturalistic studies [77], [78]. These challenges, however, are negotiated with increased success, thanks to transformative developments in affective computing [79].

In this context, we undertook a naturalistic driving study, focused on the identification and estimation of cardiovascular activation in commutes and other routine drives. A key motivation was to use this as a starting point for unearthing any sympathetic activation lurking in ubiquitous machine usage. There are two practical questions underlying our research: 1) how to measure cardiovascular activation and 2) what factors to track to identify any likely linkages to sympathetic activation.

With respect to the first question, we adopted heart rate as the key measure of cardiovascular activation for the following reasons: a) heart rate correlates with arousal [55]; b) heart rate is an important health indicator [80], linked to long-term cardiovascular [81] and mental health [82] problems; and c) heart rate can be reliably measured with smartwatches [83], a ubiquitous sensor worn by over a quarter of the U.S. population [84].

With respect to the second question, we included driving behaviors, and extrinsic as well as intrinsic factors associated with these behaviors. In terms of behaviors, we tracked the drivers' speed, acceleration, and habitual texting. In terms of extrinsic factors, we tracked the traffic and weather patterns the drivers encountered while driving. In terms of intrinsic factors, we accounted for the drivers' gender, anxiety, and personality traits. All the said factors have support in the literature, as explained in sections 2.2.1, 2.2.2, and 2.2.3, facilitating a comprehensive and meaningful investigation.

Our study has three elements that make it stand out from other naturalistic driving studies [18], [22]. First, we systematically capture behavioral cycles at the weekly and daily levels, by shadowing participants for a full week, day and night, without any interruption. Human behavior - either in driving or non-driving contexts - is largely periodic for practical and other reasons [32]. It is in the repetition of this periodicity, where the long-term concerning effects of some physiological responses may lie. Second, we do not only capture the driving but also the complementary non-driving physiology of participants. This provides a comparative control, which helps to delineate heart correlations unique to driving from heart correlations that apply across driving and non-driving activities. Third, in our study, participants go about their daily lives emitting data through their own smartphones and smartwatches. This is in contradistinction to 'given' phones and watches in other studies, which may introduce behavioral modifications hard to appreciate.

Analysis of multimodal data from 21 young but experienced drivers provides insightful results that highlight the virtues of our study design. In more detail, we found that anxiety predisposition is associated with significantly higher heart rates in driving. We did not find any such association in non-driving activities. Our working hypothesis about this phenomenon is that although driving is a ubiquitous activity, it has risk. Activities that involve even small risk tend to trigger hyperarousals to people with naturally high anxiety levels [85], which manifest as elevated heart rates, with all other things being equal.

We also found that higher speeds are associated with higher heart rates. For instance, freeway speeds are accompanied by significant heart rate loading with respect to city speeds, all other things being equal. One possible explanation for this finding is as follows: When people drive a car, they are in charge of a multi-ton machine. The higher the speed of this machine, the higher its momentum and thus, the danger it poses. It is simple physics, to which experienced drivers may have consciously adjusted, but it appears that subconsciously their physiology continues to produce 'fight or flight' responses.

Interestingly, we did not find any association between traffic or weather and cardiovascular activation while driving. This result, however, may be an artifact of our dataset; for example, if we had data from New York both in the summer and winter, traffic and weather may have emerged as additional cardiovascular activators. In contradistinction, our study took place in a Southwestern state in the summer, where the weather is typically good. Indeed, over 95% of the trips under investigation took place under clear or cloudy weather (Fig. 2b), which is perfect for driving. Furthermore, the great majority of these trips featured mean Jam Factor between 1 and 4 (Fig. 2b), suggestive of good traffic conditions. There are two main reasons for the preponderance of relatively unhindered traffic flow in our dataset: First, some of the participants were coming from mid-size cities, like College Station, TX (Fig. 1), where traffic is rarely a problem. Second, even for participants from major Texas cities, like Houston and Dallas (Fig. 1), traffic conditions are far better than other major cities in the U.S., like Los Angeles and New York. Hence, our study can be viewed almost as a natural experiment, with subdued exogenous factors, which allows the importance of endogenous factors to come to the fore.

In fact, the endogenous nature of our findings makes them all more important. If the cardiovascular activators were exogenous, such as weather and traffic, one could avoid them with some planning. However, people cannot avoid their own nature (i.e., being anxious) and cannot avoid speed when they drive. After all, this is the main reason for using cars, that is, to move fast from point A to point B. Hence, speed-related cardiovascular activation is innate to car usage. The effects suggested by our model are sizeable. A person with anxious predisposition (TA = 50) who drives at freeway speeds (65 mph) is associated per our model with 5 BPM and 4 BPM heart rate premiums, respectively, for a total of 9 BPM. It is not desirable to exhibit such excessive activation, while sitting, for an hour or more every day. If people can avoid or minimize relevant driving activities, they probably should.

A more difficult question is if such daily cardiovascular activation poses any long-term risk. Our model has been constructed from data of people who drive 1-2 hours daily and have been doing so for about 10 years. Driving for our participants is not a novelty, but they are not professional drivers. We do not know if the said heart rate premiums would hold for professional drivers who drive all the time, and a separate study would be needed for that. If they do hold, however, these effects may have long-term health implications, because they would be on par with risk factors described in the Framingham Heart Study (FHS) [86]. For instance, analyzing data from FHS, researchers found that a sustained increase in daily heart rate by 11 BPM, increases the risk of cardiovascular disease by 15% [87].

Thanks to our all encompassing study design, we were also able to establish that highly conscientious people are associated with higher heart rates not only when they drive but also in other nondescript activities they engage in. It is not easy to do the right thing, and presumably this is what conscientious people tend to do all the time [88]; for instance, by remaining extra vigilant when they drive to ensure the safety of all involved, or by taking the ‘extra mile’ in their office or home duties. We also measured male participants to have significantly higher heart rate than female participants across driving and non-driving activities. For ages below 30, which is the age range of our sample, this finding is well-supported in the medical literature [89].

With regard to weekdays (vs. weekends) and afternoons (vs. mornings), we found cardiovascular activation to persist across both driving and non-driving activities. For the afternoons, medical researchers documented that parasympathetic activity in the afternoon undergoes significant reduction [48], which explains the higher observed heart rate in our study. This result poses larger questions related to work-life balance and flexible work schedules. As afternoons appear to impose an onerous cardiovascular load on whatever people do, possible solutions include shortening workdays, or alternatively interrupting them with a big break after lunch, only to resume early in the evening. For the latter, there is precedence in certain cultures centered around the concept of ‘siesta’ [90].

An important question is if the observed cardiovascular activation is linked to sympathetic activation (arousal) or parasympathetic reduction. We believe the likely answer to this varies depending on the factor. For the association of cardiovascular activation with afternoon activities, parasympathetic reduction is the most likely contributor, something that as we mentioned is supported by the literature [48]. However, for the association of cardiovascular activation with trait anxiety and car speed, the most likely contributor is sympathetic activation. Anxiety is intimately linked to sympathetic activation [64]. As for speed, because it is perceptible through the senses, again sympathetic activation is the most likely underlying source of cardiovascular activation [91]. All these parasympathetic/sympathetic linkages are based on circumstantial evidence and thus, further research is needed to clarify the origins of the observed cardiovascular activation. What is far more certain and remarkable, however, is that straight forward driving, with little traffic and in good weather, has the potential to generate significant cardiovascular activation, adding to the trials and tribulations of daily life. Affective computing and ubiquitous technologies provide for the first time the opportunity to track such activation, and the present study could be viewed as proof of concept.

4.1 Limitations

Our study tracks cardiovascular activation through heart rate only. This makes us rely on circumstantial evidence for delineating the relative contribution of sympathetic activation vs. parasympathetic reduction. The addition of heart rate variability (HRV) in the set of physiological measures would contribute to further clarification of the sympathetic vs. parasympathetic origins of the observed cardiovascular activation [92]. Unfortunately, current Apple Watches record heart rate variability very infrequently (i.e., 3-4 times per day) to be useful in a real-time study such as this.

In this work, we have pursued trip level analysis, which is sufficient for determining major physiological effects at the macroscopic level. Nevertheless, analysis at a finer temporal resolution level (for instance, every driving minute) would likely yield additional insights for transient effects that have probably been absorbed in the mean trip computations. For example, heavy traffic conditions during a small portion of a trip (Fig. 3) most likely affect heart rate, but the effect may be diluted at the trip level. As we publicly release the study’s voluminous dataset [https://github.com/UH-CPL/NUBI-DRIVE-1], affective computing and other researchers will have the opportunity to pursue detailed temporal resolution analysis not covered in the present paper.

Because this study was conducted during the summer months in a southwestern state, the weather was usually fair, undercutting the opportunity for a comprehensive estimation of this predictor. The same applies for the traffic predictor, as traffic flow was relatively unhindered in the great majority of the recorded trips . Furthermore, by design our study has been constrained to young adults, to neutralize age as a group factor and thus reduce the number of needed participants. The implication of this choice, however, is that our results may not be applicable to other segments of the population, such as older adults, and separate studies would be needed for these groups.

While all these restrictions may appear to reduce the generality of our study, this is only partly true. The study’s aim was the investigation of sympathetically induced cardiovascular activation in daily commutes. Our analysis demonstrated that even under the most favorable conditions - i.e., good weather, light traffic, and healthy experienced young drivers - sympathetic arousal has significant presence in routine drives. One would expect that this can only get worse under unfavorable conditions, such as bad weather, heavy traffic, and inexperienced drivers. Hence, our study is the most minimalist arousal scenario, providing a broadly useful baseline. While not harming generality very much, the study’s design restrictions contribute to reducing bias, because they ensure a relatively homogeneous sample. This bias reduction is further served by the inclusion of participant-centered random effects in the models - see term $1|S$ in Eq. (2) - where the error associated with random participant selection is taken into account.

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MD Tanim Hasan received his B.S. in Computer Science from the Islamic University of Technology, Dhaka, Bangladesh in 2010. Subsequently, he worked in the software industry for six and a half years. Since 2019 he has been pursuing his Ph.D. at the Affective and Data Computing Laboratory of the University of Houston, where he is currently a Ph.D. candidate. His research interests are in affective computing and data science. Hasan has worked in multiple research projects funded by the National Science Foundation and the Texas A&M Transportation Institute. He has published in ACM CHI and other venues.

Huda Alghamdi Huda Alghamdi is a Ph.D. student at the Affective and Data Computing Laboratory of the University of Houston. She also holds a teaching assistant position in the Faculty of Computing and Information Technology at King Abdul-Aziz University, Jeddah, Saudi Arabia. She received her B.S. degree in Computer Science from Al-Baha University, Al-Baha, Saudi Arabia in 2013, and her M.S. degree in Computer Science from Nova Southeastern University, Davie, FL in 2019. Alghamdi's research interests include affective computing, IoT, and cyber-physical systems.

Salah Taamneh is currently an Associate Professor at the Department of Computer Science and Applications, Hashemite University, Zarqa, Jordan. He received his B.S. degree in Computer Science from Jordan University of Science and Technology, Irbid, Jordan in 2005, his M.S. degree in Computer Science from Prairie View A&M University, Prairie View, Texas in 2011, and his Ph.D. degree in Computer Science from the University of Houston, Houston, Texas in 2016. His research interests are in affective computing and data visualization. Notably, Dr. Taamneh was the developer of Subject Book, one of the first visualization tools for mulitmodal datasets.

Michael Manser received his Ph.D. degree from the University of Minnesota. He is a senior research scientist and human factors program manager in the Center for Transportation Safety (CTS), Texas A&M Transportation Institute. His work examines the behavioral, cognitive, and perceptual driver-related factors that contribute to transportation safety, mobility, and efficiency. His main focus is on the interaction between drivers, vehicles, and infrastructure-based technology. He has more than 20 years of research experience, having served multiple times as Principal Investigator in projects of the National Highway Traffic Safety Administraiton (NHTSA). Dr. Manser has authored numerous articles on human factors and transportation topics.

Robert Wunderlich received the B.S. and M.S. degrees in Civil Engineering from the University of Tennessee and is a licensed professional engineer in Texas. He is the director of the Center for Transportation Safety, Texas A&M Transportation Institute. The center's work is focused on developing safer roadways and safer drivers through research and outreach programs funded at nearly $5 million each year. He is responsible for leading the various research programs for the center, which was established by the Texas Legislature, in 2001. He has over 35 years of experience in transportation safety and engineering in the municipal, private sector and research fields, and is dedicated to enhancing the capacity of transportation professionals to improve traffic safety. He is a past international president of the Institute of Transportation Engineers (ITE) and was named the Transportation Engineer of the Year by the Texas District of ITE, in 2007.

Panagiotis Tsimayrtzis received the B.S. degree in Mathematics from the Aristotle University, Thessaloniki, Greece, and the M.S. and Ph.D. degrees in Statistics from the University of Minnesota, where he served as a visiting faculty member in 2000. In 2004, he joined the Department of Statistics, Athens University of Economics and Business, where he is currently an Associate Professor. He also holds an Associate Professor position at the Department of Mechanical Engineering in Politecnico di Milano. Dr. Tsiamyrtzis' research interests include statistical aspects of affective computing, statistical process control, and applications of Bayesian statistics. He was the recipient of the Best Student Paper Award in the 2000 Meeting of the American Statistical Association.

Ioannis Pavlidis is the Eckhard-Pfeiffer Distinguished Professor of Computer Science and Director of the Affective and Data Computing Laboratory at the University of Houston. Prior to joining the University of Houston, he worked for six years as senior principal research scientist at Honeywell Labs. Dr. Pavlidis holds Ph.D. and M.S. degrees in Computer Science from the University of Minnesota, an M.S. degree in Robotics from Imperial College, and a B.S. degree in Electrical Engineering from Democritus University. His research has been funded by the National Science Foundation, transportation agencies, and medical institutions. He has published extensively in the areas of affective computing, data science, and science of science. He was the first to conceive and develop contact-free methods for measuring physiological variables, including electrodermal activity, breathing, and heart function, which he used to study stress.