

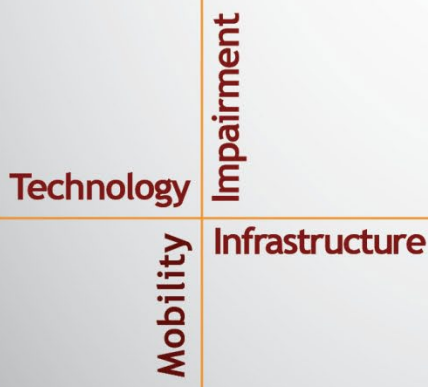
NSTSC

National Surface Transportation Safety Center for Excellence

Effectiveness of Wearable Devices to Study Driving Stress of Long-haul Truck Drivers in Naturalistic Driving Systems

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EXECUTIVE SUMMARY

Advancements in wearable technology, driven by innovations in artificial intelligence and the Internet of Things, have significantly expanded our ability to monitor health and safety in various domains, including transportation. In this age of big data, the continuous collection and analysis of physiological data from wearable devices has opened new avenues for enhancing road safety and driver well-being. This report investigates the feasibility and effectiveness of using wearable technology to monitor fatigue and stress levels among long-haul commercial motor vehicle drivers. The goal of this research is to reduce risks associated with drowsy driving, which is a significant contributor to road accidents worldwide (M. Islam & Mannering, 2023).

Wearable technologies, such as the Empatica EmbracePlus smartwatch, offer a promising approach to real-time health monitoring by providing continuous insights into drivers' physiological states. This study was designed to evaluate the capability of these devices to detect early signs of fatigue and stress, understand the various factors affecting a driver's well-being, and identify strategies to manage these issues effectively. A repeated measures study design was implemented, collecting comprehensive health data from a sample of 10 long-haul drivers over a 5-day period (i.e., 1 work week), with one driver providing additional data over an extended 4-week period. Data collection involved continuous monitoring of physiological signals, such as heart rate variability and electrodermal activity, supplemented by self-reported information on stress levels, traffic conditions, diet, and other relevant variables through daily questionnaires.

The findings from this study highlight the potential of wearable technology to transform driver safety and health management practices. The data collected provided valuable insights into the drivers' daily experiences and behaviors, revealing patterns related to stress levels, dietary habits, hydration practices, and coping mechanisms. Most participants experienced mild to moderate stress, influenced significantly by traffic conditions and driving durations.

The report indicates that wearable technology can provide key insights by enabling continuous monitoring of fatigue and stress levels; this then suggests a potential for early alerts for necessary breaks and prevention of accidents due to drowsy driving. Furthermore, the data generated by these devices can be used to develop personalized interventions that can improve drivers' health and work conditions. For successful implementation, it is important to address concerns regarding data privacy and usability while creating an environment that encourages the adoption of such technology. Encouraging awareness about the applications of wearable devices and their capabilities in monitoring health information could create such an environment. Future research should focus on refining wearable technologies to enhance user comfort, maintain data security, and explore broader applications within transportation safety related to long-haul drivers.

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LIST OF ABBREVIATIONS AND SYMBOLS

ANS	autonomic nervous system
CMV	commercial motor vehicle
ECG	electrocardiogram
EDA	electrodermal activity
EEG	electroencephalogram
FDA	Food and Drug Administration
FLFNN	functional-link-based fuzzy neural network
GSR	galvanic skin responses
HF	high frequency
HRV	heart rate variability
iPPG	imaging-based PPG
Ivrr-PPG	illumination variation robust remote-photoplethysmography
IQR	interquartile range
kNN	k-nearest neighbors
LF	low frequency
MLP	multilayer perceptron
NHTSA	National Highway Traffic Safety Administration
NIR	near-infrared
PFT	pulmonary function testing
PPG	photoplethysmogram
SpO2	oxygen saturation
SVM	support vector machine
VTTI	Virginia Tech Transportation Institute
WPT	wavelet packet transform
μS	microsiemens

CHAPTER 1. INTRODUCTION

Fatigue and drowsiness are among the leading causes of road accidents worldwide, posing a significant threat to road safety (M. Islam & Mannering, 2023). According to data from the National Highway Traffic Safety Administration (NHTSA), drowsy driving was implicated in approximately 91,000 police-reported crashes in 2017, resulting in an estimated 50,000 injuries and nearly 800 deaths (NHTSA, 2022).

However, these figures likely represent only a portion of the problem. Research by the AAA Foundation for Traffic Safety suggested that the true number of crashes attributable to drowsy driving annually could be as high as 328,000, with about 109,000 resulting in injuries and 6,400 in fatalities (Tefft, 2014). Given the immense danger that driver fatigue presents on our roads, maintaining alertness among long-haul truck drivers is especially important, as they spend long hours driving as part of their occupation. According to the Federal Motor Carrier Safety Administration (FMCSA), large truck crashes accounted for 4,965 fatalities and 146,930 injuries in 2020, with driver fatigue being one of the major contributing factors (FMCSA, 2022). Thus, their health and attentiveness are critical not just for their own safety but for all motorists sharing the road.

In the context of long-haul trucking, drivers are particularly vulnerable to the risks associated with fatigue (Onninen et al., 2022). Extended periods of driving, irregular sleep patterns, and the constant pressure to adhere to demanding delivery schedules are typical in their line of work (Mabry et al., 2023; Solomon et al., 2004). These challenges are compounded by environmental and lifestyle factors, such as the scarcity of healthy food options along highways and the sedentary nature of truck driving. Poor eating habits and the lack of physical activity not only contribute to the deterioration of physical health but also exacerbate fatigue, thereby affecting alertness and reaction time.

According to NHTSA (2022), crashes due to drowsiness occur most frequently between midnight and 6 a.m., or in the late afternoon, times when the human circadian rhythm naturally dips. The circadian rhythm—our internal clock that regulates sleep—plays a significant role in determining alertness levels. For long-haul drivers, who often drive during these critical hours, understanding and managing the impact of circadian rhythm on fatigue is essential. Continuous monitoring of drivers' alertness levels and overall health thus becomes a necessity to ensure safety. Wearable technologies present a promising solution in this regard. By continuously tracking biometrics such as heart rate, physical activity levels, sleep patterns, and stress indicators, these devices can unobtrusively monitor driver health and well-being in real time. The data provided by wearable devices can enable the early detection of emerging health issues, such as heart attacks, which may affect driving performance.

Wearable devices are particularly effective for driver monitoring because they can track the autonomic nervous system (ANS), which comprises the sympathetic and parasympathetic nervous systems. The sympathetic nervous system prepares the body for stressful or high-energy activities, often referred to as the “fight or flight” response (Glick et al., 1965). It increases heart rate, dilates the pupils, and redirects blood flow to muscles, thereby priming the body for action. On the other hand, the parasympathetic nervous system is responsible for the “rest and digest” functions, promoting relaxation, reducing heart rate, and facilitating digestion. Together, these

systems regulate crucial physiological functions that are indicators of a driver's state of alertness and overall health.

By monitoring metrics such as heart rate variability (HRV), wearable devices provide insights into the balance between the sympathetic and parasympathetic nervous systems (Lu et al., 2022). For example, a high HRV generally indicates a dominant parasympathetic response, suggesting the driver is relaxed and well-rested. Conversely, a low HRV can indicate a dominant sympathetic response, which may signal stress or fatigue. Continuous tracking of these metrics allows wearable devices to detect early signs of fatigue or stress, prompting drivers to take necessary breaks and thereby enhancing road safety. Additionally, unlike self-reported surveys, which can be subjective and prone to falsification, data from wearable devices provide an objective and reliable measure of the driver's physiological state. This ensures more accurate monitoring and timely interventions.

Truck drivers face numerous challenges that affect their health and safety on the road. Short-term issues include acute fatigue and reduced alertness due to long driving hours and irregular sleep patterns (Zhang et al., 2024; Mabry et al., 2022; Huhta et al., 2021). These conditions are exacerbated by the sedentary nature of their job, leading to immediate health problems like back pain and joint issues (Ramroop et al., 2021; Chen et al., 2024). In the long term, truck drivers are at risk of developing chronic conditions such as obesity, hypertension, and diabetes due to poor eating habits and lack of physical activity (Lemke et al., 2023). The constant pressure to meet tight delivery schedules adds to their stress, contributing to both short-term fatigue and long-term health deterioration (Guest et al., 2020).

Wearable devices can address these challenges by providing real-time and continuous monitoring of the ANS. In the short term, they can alert drivers to take breaks when signs of sympathetic dominance, such as increased heart rate or reduced HRV, are detected (Persson et al., 2020). This helps prevent accidents caused by fatigue and stress. Long-term health management is also supported by wearable devices through the collection and analysis of data on physical activity, sleep patterns, and heart rate. Furthermore, by supplying drivers with objective data about their lifestyle and health metrics, wearable devices can promote positive behavioral changes towards a better lifestyle. Research has indicated that the self-monitoring and feedback enabled by wearable devices can motivate individuals to engage in healthier eating (Prioleau et al., 2017), exercise, and sleep regimens (Miller, 2017; Schlomann et al., 2016). Thus, leveraging wearable technologies is a practical approach to enhancing long-haul truck driver wellness and alertness through preventive health management.

The role of wearable devices extends beyond individual health tracking. These devices are instrumental in advancing a data-driven approach to healthcare, offering critical insights into drivers' daily habits and overall health. Such data are invaluable for healthcare professionals in customizing health recommendations and interventions, thereby enhancing the effectiveness of health management strategies. Additionally, insights from wearable data can lead to developing countermeasures for road accidents through early detection of fatigue. Real-time analytics drawn from wearable devices can potentially provide actionable insights on various fatigue measures, which could help prevent road accidents caused by driver fatigue and contribute to greater road safety and public well-being.

FACTORS AFFECTING SUCCESSFUL ADOPTION OF WEARABLE DEVICES

Integrating wearable technologies into long-haul trucking represents a significantly positive move towards enhancing road safety and driver well-being. However, the successful implementation and acceptance of these devices among long-haul drivers hinges on several factors, including the perceived usefulness of the product, ease of usability, self-expressiveness, and concerns regarding privacy.

Perceived Usefulness and Usability

The adoption of wearable technology in the trucking industry largely depends on how drivers perceive its usefulness. If they see the technology as beneficial in improving their health, safety, and overall job performance, they are more likely to embrace it (Greenfield et al., 2016). Additionally, the ease of using these devices plays a crucial role. Wearable devices that are user friendly and integrate seamlessly into the daily routines of truck drivers are more likely to gain acceptance (Peng et al., 2022).

Perceived Self-Expressiveness

As Peng et al. (2022) highlighted, the degree to which a technology reflects an individual's personal characteristics, known as perceived self-expressiveness, is an important determinant in wearable adoption. For truck drivers, this might involve wearable devices that are not only functional but also resonate with their personal style or professional identity.

Perceived Privacy Risk

Privacy concerns are a significant barrier to the adoption of wearable technology. The apprehension about how personal health data are collected, stored, and potentially shared can deter drivers from using these devices (Kapoor et al., 2020). One of the main concerns is the use of cloud storage for data management. When data are transmitted and stored in the cloud, there are inherent risks associated with data breaches, unauthorized access, and data misuse. Addressing these concerns through stringent data privacy policies, such as end-to-end encryption and regular security audits, and transparent communication about how data will be protected and used is essential for widespread acceptance. Ensuring that drivers are fully informed about the security measures in place, and providing clear guidelines on data ownership and access, can help build trust and encourage the adoption of wearable technologies.

Performance Improvement vs. Surveillance Concerns

Another critical factor is the balance between performance enhancement and the perception of surveillance. Wearable technologies can monitor drivers' health and performance, providing data that can improve safety and efficiency. However, if drivers feel that these devices are being used to surveil their behavior excessively, it may lead to resistance (Levy, 2015). Ensuring that the primary purpose of these technologies is to support and enhance driver well-being, rather than to control or monitor them unnecessarily, is vital for their acceptance.

Role of Awareness in Wearable Technology Adoption

An important aspect of promoting the adoption of wearable technology among long-haul truck drivers is awareness. Educating drivers about the benefits of wearable devices, how they work, the type of data they collect, and the measures taken to protect their privacy is crucial (Suwondo, 2022). Awareness campaigns can demystify technology, alleviate privacy concerns, and showcase the potential health and safety benefits. This research aims not only to explore the potential of wearable technologies in enhancing driver safety and health but also to understand the factors influencing their acceptance among long-haul truck drivers. As such, an important part of this research involves understanding the ease of wearing these devices while driving. The scope of wearable devices in driver health monitoring, along with understanding the ease/comfort while wearing these devices, will help ensure that the benefits of wearable technology are fully realized, leading to healthier lifestyles for drivers and safer roads for all.

CHAPTER 2. WEARABLE DEVICES

In the pursuit of enhancing road safety through advanced technology, significant efforts have been made in the domain of fatigue and driver health monitoring. Among these, non-invasive techniques are garnering increasing interest due to their user-friendly nature and minimal disruption to the driver's routine. Non-invasive methods, such as wearable devices and eye movement monitoring systems, offer promising solutions for real-time fatigue detection without the need for intrusive procedures or equipment.

EMERGENCE OF NON-INVASIVE FATIGUE MONITORING TECHNIQUES

Non-invasive fatigue monitoring techniques represent a significant advancement in the field of driver safety (Halin et al., 2021; Zilberg et al., 2022). These methods are designed to assess a driver's alertness and overall health status without the need for direct physical contact or invasive measures. The appeal of these technologies lies in their ability to seamlessly integrate into the driver's environment, providing critical data without disrupting the driving experience or causing discomfort to the user. A notable example of non-invasive technology is the use of eye- and iris-based sensors for drowsiness detection. These camera-based eye- and iris-tracking sensors analyze eye movements, blink patterns, and pupil dilation to identify signs of fatigue (Michelaraki et al., 2023). Changes in blink rate, slower eye movements, and increased blink duration are some of the key indicators these systems track. The data captured by these sensors are processed through sophisticated algorithms, enabling real-time evaluation of the driver's alertness levels.

Similarly, camera-based systems are also used in monitoring heart rate and similar vital signs in drivers (Sarkar et al., 2014). Camera-based systems utilize advanced imaging and algorithmic techniques to detect subtle changes in a person's appearance that correlate with vital signs like heart rate (Li et al., 2023; Sarkar et al., 2014). These changes, often imperceptible to the human eye, can include slight variations in skin tone due to blood flow. By analyzing these changes, camera-based systems can estimate heart rate and other related metrics without any physical contact with the driver.

LIMITATIONS OF CAMERA-BASED MONITORING SYSTEMS

While non-invasive fatigue monitoring techniques show promise for improving driver safety, they are not without limitations. These limitations affect their efficacy, user acceptance, and overall practicality in real-world scenarios.

Environmental Sensitivity and Reliability

Both eye- and iris-based sensors and camera-based systems are highly sensitive to environmental conditions. The accuracy of these systems can be significantly affected by factors such as lighting variations, which are common in driving environments. For instance, changing light conditions throughout the day or artificial light sources inside the vehicle can interfere with the sensors' ability to accurately track eye movements or detect skin tone changes. This sensitivity can lead to inconsistent data and, in some cases, false alarms or missed detections of fatigue or other health indicators.

User Acceptance and Comfort

The acceptance of these technologies by drivers is a crucial factor in their effectiveness. Some users may find continuous monitoring through eye- and iris-based sensors to be intrusive or uncomfortable, particularly over long periods. Similarly, the idea of being constantly recorded by a camera for vital sign monitoring might raise concerns about privacy and personal space. These apprehensions can lead to resistance in adopting these technologies, undermining their potential benefits for improving road safety.

Privacy and Data Security Concerns

The use of biometric data for continuous monitoring raises significant privacy concerns. Both eye/iris sensors and camera-based systems involve collecting and processing sensitive personal data. There are apprehensions about how this information is stored, accessed, and potentially misused (Wells and Usman, 2024; Wang et al., 2023). In an era where data privacy is a major concern, the fear of surveillance and data misuse can be a considerable barrier to the widespread acceptance of these monitoring systems.

Technical Complexity and Implementation Costs

Implementing these advanced monitoring systems in vehicles involves a high level of technical complexity. The need for sophisticated hardware and software, along with the integration of these systems into the vehicle's design, can be challenging. Additionally, the costs associated with developing, installing, and maintaining these systems can be prohibitive, particularly for widespread deployment across large fleets of commercial vehicles.

Adaptability and Versatility

The adaptability of these systems to different types of vehicles and driving conditions is another concern. The effectiveness of eye- and iris-based sensors and camera-based systems can vary based on the vehicle's design, the driver's seating position, and other ergonomic factors. Moreover, these systems may need to be tailored for different driving scenarios and individual user characteristics, adding to the complexity of their deployment.

WEARABLE DEVICES FOR COMPREHENSIVE HEALTH MONITORING

In contrast to the challenges faced by non-invasive fatigue monitoring systems like eye- and iris-based sensors and camera-based systems, wearable devices offer a more versatile and user-friendly approach to health monitoring. These devices employ a variety of techniques to provide comprehensive insights into a driver's health, making them a valuable tool in combating driver fatigue and related health issues. Wearable devices utilize a range of methods to monitor different aspects of health, each with its own unique approach and benefits.

Electrocardiogram

Electrocardiogram (ECG)-based wearable devices use electrodes to detect the electrical activity of the heart. This method provides valuable data on heart rate, rhythm, and overall cardiac health, which can be crucial in identifying stress or fatigue-related anomalies in drivers. The data

obtained from ECG sensors can offer detailed insights into the ANS, comprising the sympathetic and parasympathetic nervous systems.

ECG technology captures the heart's electrical signals, providing a precise measure of heart rate and rhythm. Variations in these signals can indicate shifts between sympathetic and parasympathetic dominance. For example, during periods of high stress or fatigue, ECG readings might show increased heart rate and decreased HRV, indicating higher sympathetic activity and a "fight or flight" response. During relaxation, ECG readings would show a lower heart rate and higher HRV, reflecting parasympathetic dominance and a state of relaxation. Matsuda and Makikawa (2008) showed that it is feasible to collect ECG readings while driving. The authors proposed an ECG monitoring system for a car driver using a capacitively-coupled electrode. This capacitively-coupled electrode, on which an operational amplifier was mounted, was embedded inside a seat to measure ECG signals. A ground electrode was placed on a steering wheel (i.e., the ECG signal was amplified by a single-ended amplifier). Subjects wore their regular suits and pants made of wool, and ECG information was obtained while they were driving at low speed on a rough road with one corner. Results showed that this system can be used to obtain ECG information while driving at low speed except for some motion artifacts caused by the steering operation, road surface, braking, and accelerating. A key focus was on detecting R peaks, which are part of the QRS complex in the ECG signal. The QRS complex represents the electrical activity when the heart's ventricles contract, and it consists of three parts: the Q wave (a small downward deflection), the R wave (a tall upward peak), and the S wave (a downward deflection following the R wave). The R peak, the highest point in this complex, is crucial for determining heart rate. Using the amplifier setup between the driver's seat and hands on the steering wheel, R peaks were detectable. On the straight section, which included bumpy road, Matsuda and Makikawa showed that R peaks could be detected after digital filtering. Digital filtering successfully reduced the impact of motion artifacts caused by rough road conditions, allowing for the detection of R peaks. However, in instances of significant motion artifacts, such as those caused by sharp steering maneuvers or sudden braking, detecting the R peaks remained challenging.

Murugan et al. (2020) conducted a similar study on the effectiveness of an ECG electrodes-based wearable device in understanding various driver states like drowsiness, visual inattention, and cognitive inattention. For data collection, ECG electrodes were placed on drivers' left and right wrists to record the signals. The experimental setup was indoors and based on a simulator. The "normal" state data were collected during an initial 15 minutes of driving, after which "visual inattention" was induced by sending SMS messages three times, to which each driver had to respond while driving. Drivers were asked simple questions pertaining to (i) an unforgettable moment in their life, (ii) something about their country, (iii) reasons for road accidents, and (iv) something they like or dislike, etc., to visually distract them from driving. Then, the driver was allowed to drive for the next 15 minutes. After that, they were asked mathematical questions (addition and subtraction) with increasing complexity, which made them think and reply while driving. This process captured data on "cognitive inattention." After this, drivers were asked to continuously drive for 80 minutes or until they fell asleep. The session stopped once the driver was unable to control falling asleep. From the collected ECG signals, a total of 20 features, including 14 time domain linear features (mean, median, standard deviation, first quartile, second quartile, third quartile, interquartile range [IQR], maximum, minimum, variance, skewness, kurtosis, root mean square, power and energy) and three frequency domain nonlinear features

(approximate entropy, central tendency measure [nanmean, trimmean, harmonic mean], and Hurst exponent) were extracted from the filtered ECG signals. The 13 most statistically significant features were extracted using analysis of variance. The overall detection accuracies for two classes—such as normal–drowsy, normal–visual inattention, normal–fatigue, and normal–cognitive inattention—were 100%, 93.1%, 96.6%, and 96.6%, respectively. The results showed that two-class detection provides better accuracy among different states. However, the classification accuracy using an ensemble classifier decreased to 58.3% for five-class detection (Murugan et al., 2020).

Photoplethysmogram

Photoplethysmogram (PPG) technology in wearable devices uses light-based sensors to measure the rate of blood flow or blood oxygen levels. This method is particularly effective for monitoring heart rate and blood oxygen saturation (SpO₂), offering insights into the driver's circulatory system. The data obtained from PPG sensors can also provide valuable information about the ANS. Koh et al. (2017) proposed a method for detecting drowsiness using PPG signals measured from fingers and earlobes. They analyzed the low frequency (LF), high frequency (HF), and LF/HF ratio values from PPG signals to detect drowsiness in drivers. Experiments were conducted with 20 subjects using a driving simulator. PPG signals were measured from fingers using a commercial device and from earlobes using a custom-designed head support. Out of 20 subjects, drowsiness was detected in 14 using finger PPG signals. Of those 14, drowsiness was also detected in eight using earlobe PPG signals. Analysis showed that during drowsy states compared to alert states (i) LF values decreased; (ii) HF values increased; and (iii) LF/HF ratios decreased. Statistical analysis confirmed significant differences in these PPG parameters between drowsy and alert states. The earlobe measurements using the custom head support were less reliable, only working for eight out of 14 drowsy cases, likely due to movement artifacts and poor sensor contact.

Similarly, Sari and Huang (2016) presented a two-stage intelligent model for detecting driver drowsiness using PPG signals. They proposed a solution that combines wavelet packet transform (WPT) and functional-link-based fuzzy neural network (FLFNN). The model uses a pulse sensor attached to the driver's fingertip to collect PPG signals, offering a more comfortable alternative to traditional ECG methods. In the first stage, WPT is employed to decompose the PPG signal into frequency bands and extract HRV features, including LF, HF, and the LF/HF ratio. These features are then fed into an FLFNN classifier in the second stage to determine the drowsiness level. Similar to Koh et al. (2017), Sari and Huang (2016) reported that their model showed significant differences in energy levels of LF and LF/HF ratio between normal and drowsy states, indicating its effectiveness.

In recent years, imaging-based PPG (iPPG) has emerged as a promising non-contact alternative to traditional contact-based PPG sensors for monitoring physiological signals (Wang et al., 2016). This technique uses standard digital cameras to detect subtle color changes in the skin caused by blood flow, effectively reconstructing the PPG signal without physical contact. For driver drowsiness detection, iPPG offers several advantages: it is non-invasive, allowing continuous monitoring without requiring drivers to wear sensors or maintain contact with specific surfaces; it enables uninterrupted measurement throughout the driving session; and it can potentially provide information on multiple parameters beyond heart rate, such as respiration rate

(Wallace et al., 2022) and blood SpO₂ (Mathew et al., 2023). iPPG can be easily integrated into vehicles already equipped with driver-facing cameras, which are becoming increasingly common for various driver assistance features. Advanced iPPG algorithms can also compensate for head movements and changing lighting conditions, making them suitable for real-world driving scenarios.

Trenta et al. (2019) developed an advanced motion-tracking system using deep learning to monitor car driver drowsiness. Their approach analyzes facial micro-movements and color changes due to blood circulation to reconstruct the PPG signal and extract facial landmarks. The system combines long short-term memory neural networks to reconstruct the PPG signal from facial landmark time-series data and convolutional neural networks to classify driver facial images as drowsy or wakeful. Trenta et al. collected data from 71 subjects, including PPG signals and facial video recordings in wakeful and drowsy states. Results showed a strong correlation between the reconstructed PPG signal from facial landmarks and the original sensor-measured PPG signal, with the system able to discriminate between drowsy and wakeful states with near 100% accuracy.

Similarly, Xu et al. (2023) proposed a novel method called illumination variation robust remote-photoplethysmography (Ivrr-PPG) to monitor drivers' heart rates during on-road driving. The system utilizes a monochrome camera with a 940-nm narrowband near-infrared (NIR) filter and two 940-nm NIR light sources to collect real-time video of drivers. The authors developed a new signal model based on a dichromatic model to account for the nonlinear relationship between illumination changes and the rPPG signal. They used a background region to sense illumination changes and suppress their impact on the pulse signal, while heart rate was estimated using a single-tone sinusoidal signal-based frequency estimation method. Experiments conducted in four different on-road driving scenarios with varying levels of illumination changes demonstrated that the Ivrr-PPG method outperforms existing single-channel narrowband NIR algorithms, especially in scenarios with dramatic illumination variations. The system achieved better root mean square error and percentage of time error less than 6 bpm scores compared to the previous state-of-the-art SparsePPG method (Xu et al., 2023).

Furthermore, Wu et al. (2017) developed a non-contact method that could accurately estimate heart rate despite the motion artifacts inherent in driving scenarios. Their approach uses a webcam to capture video of the driver's face, extracts an rPPG signal using a chrominance-based method, and then applies bandpass filtering and empirical mode decomposition to reduce noise. A k-nearest neighbors (kNN) classifier is then used to estimate the heart rate from frequency domain features. The method was tested in three scenarios: sitting casually indoors, strong artificial motion indoors, and real driving outdoors. Compared to the conventional maximum peak amplitude method, their approach significantly reduced estimation errors, particularly in the driving scenario, where mean squared error was reduced from 30.6 bpm to 2.79 bpm.

Temperature Monitoring

Wearable devices equipped with temperature sensors can track changes in body temperature, which can be indicative of various health conditions, stress levels, or the onset of illness. The assessment of drowsiness using temperature from wearable devices is a nascent area of study. However, some research has shown that driver drowsiness can be effectively detected using

thermal imaging. Tashakori et al. (2022) developed a method to detect driver drowsiness using thermal imaging, focusing on temperature changes in the forehead and cheek regions. Their study involved 30 subjects in a driving simulator, with drowsiness levels assessed by human observers and facial temperature patterns captured by a thermal camera. The research found that as drowsiness increased, forehead temperature decreased by 0.46 °C and the cheek-forehead temperature gradient decreased by 0.81 °C, while cheek temperature rose by 0.35 °C. Using machine learning classifiers like support vector machine (SVM) and kNN, Tashakori et al. achieved an 82% accuracy in drowsiness detection. The study emphasizes the efficacy of using forehead and cheek temperature, especially the gradient between them, as indicators of drowsiness. This provides guidance for using temperature as a feature in wearable devices.

Electrodermal Activity

Electrodermal activity (EDA) sensors measure the skin's electrical activity, which varies with sweat gland activity and can indicate stress or emotional arousal (Taylor et al., 2015; Poh et al., 2010; McDuff et al., 2012). These data can be used to assess a driver's stress levels and overall emotional state. Lanatà et al. (2014), through analysis of electrodermal response, demonstrated that incremental stress levels during simulated driving significantly impact the ANS responses and driving style. In their study involving 15 subjects, three driving sessions were conducted with increasing stress levels. The first stressor involved unexpected mechanical stimuli, such as sudden skids, to simulate the effects of strong wind gusts. The second added stressor combined these mechanical stimuli with time-sensitive arithmetical questions, creating an increased psychological load. Throughout these sessions, the driver's physiological signals and the vehicle's mechanical parameters were meticulously recorded and analyzed. The study found notable statistical differences in both ANS responses, such as HRV, respiration activity, and electrodermal response, and mechanical parameters like steering wheel angle corrections and velocity changes across the different stress levels.

Similarly, Amidei et al. (2022) conducted experiments using a driving simulator and a multi-sensor Empatica E4¹ wrist-worn device to monitor physiological parameters, focusing on skin conductance changes to detect driver drowsiness. The experiment, involving nine healthy subjects across various age groups, was conducted in a controlled environment with an average room temperature of 23 °C. Participants were equipped with the Empatica E4 device on their dominant wrist and underwent a 40-minute driving simulation. Their alertness was periodically assessed using the Karolinska Sleepiness Scale questionnaire. Data analysis, including artifact removal, segmentation, feature extraction, and machine learning algorithm application, was performed to classify the driver's state into alert, slightly drowsy, and drowsy categories. The results demonstrated that the random forest classifier, along with other bagging and boosting-based algorithms, was the most effective, achieving an accuracy of 84.1% in identifying the different states and showcasing the potential of this approach for real-time driver drowsiness detection. This research showed that electrodermal activities can be used to monitor driver stress.

¹<https://www.empatica.com/research/e4/>

Electroencephalogram

Electroencephalogram (EEG)-based wearable devices detect electrical activity in the brain, providing data on brain wave patterns. This information can be crucial in assessing alertness and detecting signs of fatigue or drowsiness in drivers. G. Li et al. (2015) conducted a study using O1 and O2 EEG channels to detect driver alertness. They utilized various frequency domain features like theta, alpha, and beta features. The most commonly used frequency bands in EEG analysis include delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz) bands. In their approach, the ground truth data for alert and drowsy states were determined based on the percentage of eyelid closure and the frequency of adjustments made on the steering wheel. In their analysis, the best classification accuracy of 93.16% was attained using an SVM classifier, which notably relied only on the theta and beta wave features for its computations.

Similarly, Lee et al. (2014) developed a non-intrusive, mobile-device-based application for real-time detection of driver drowsiness, achieving a high accuracy rate. Utilizing EEG and respiration signals, they classified driver alertness into four categories: awake, slightly drowsy, moderately drowsy, and extremely drowsy, as determined by experienced physicians. The study focused on EEG readings from the Fpz-Cz and Pz-Oz channels, extracting features in both time and frequency domains. The application employed a Butterworth bandpass filter for EEG preprocessing and used the WPT method for feature extraction. A mutual information technique refined the feature set for efficient classification using an SVM, resulting in an impressive accuracy of 98.5%. These innovative approaches highlight the potential of using EEG signals to enhance driver safety.

Oxygen Saturation (SpO2)

SpO2 sensors in wearable devices measure the oxygen levels in the blood, providing essential information about respiratory and circulatory health. Bunde and Banerjee (2009) showed that the changes in oximetry pulse can indicate driver fatigue. They collected skin conductance and oximetry pulse signals from drivers before and after long-haul drives. Eighteen features were extracted from the signals, including mean, standard deviation, frame energy, frequency metrics, and their gradients over time. The feature data were used to train and test multilayer perceptron (MLP) neural network models to classify driver fatigue states. Single hidden layer and two hidden layer MLP networks were evaluated. The two hidden layer MLP model with hyperbolic tangent activation gave the best performance, with 93% classification accuracy for fatigue detection (Bunde & Banerjee, 2009).

Sweat Analysis

Recent advancements in wearable technology have led to the development of devices capable of analyzing sweat composition. This method can provide insights into various metabolic and physiological conditions (Gao et al., 2023). Manikandan et al. (2021) developed a system to reduce driver distractions using EEG signals in conjunction with galvanic skin responses (GSR). This approach takes advantage of the electrical properties of the skin, which are influenced by sweat gland activity and emotional behavior, to gauge a driver's condition. The GSR sensor operates by measuring the skin's resistance and conductance, utilizing the sweat glands' activity as an indicator of the user's emotional state. A minimal voltage is applied to the sensor, which,

with the help of two electrodes, passes a negligible current through the skin, ensuring safety for the user. This combined use of EEG and GSR provides a more immediate and accurate detection of distractions, aiming to reduce accidents by preemptively identifying potential distractions, which is especially effective during nighttime driving.

Similarly, Dehzangi et al. (2018) investigated the use of phasic GSR, measured via a wristband wearable device, to detect driver distractions in an on-the-road driving experiment. The study involved decomposing raw GSR signals into phasic and tonic components using continuous decomposition analysis. The phasic component, indicative of skin conductance changes, was analyzed in distracted (calling and texting) and non-distracted driving scenarios. Spectro-temporal transformations of these signals provided insights into the physiological patterns associated with distraction. Relevant spectral and temporal features were extracted and refined using SVM recursive feature elimination for efficient distraction identification. The study achieved a cross-validation accuracy of 94.81% with all features and 93.01% with the reduced feature set (Dehzangi et al., 2018). This approach demonstrates the effectiveness of using wearable GSR sensors for early detection of driver distraction with minimal privacy intrusion and faster response times.

Blood Sugar (Glucose) Monitoring

Wearable devices are also being developed to monitor blood glucose levels non-invasively, a significant advancement for drivers with diabetes or other metabolic conditions (Siddiqui et al., 2018). Though their method is not specifically for drivers, M. M. Islam and Manjur (2019) focused on addressing the challenges of invasive techniques in diabetes management by introducing a non-invasive method for blood glucose level measurement. They utilized PPG signals combined with GSR sensor data to enhance accuracy and minimize physiological variations that lead to erroneous readings. Their model incorporated data from both PPG and GSR sensors, along with traditional glucometer readings, in a deep learning algorithm to measure blood glucose levels non-invasively. Comparing their system's output with conventional invasive techniques, they found that their multi-sensor-based approach significantly improved the prediction accuracy of glucose levels, offering a cost-effective and more comfortable alternative to traditional methods. Similarly, further research advancements have shown great prospects in non-invasive glucose monitoring (Siddiqui et al., 2018; Tsai et al., 2019).

Wearable Pulmonary Function Testing Device

Wearable pulmonary function testing (PFT) devices assess lung function and respiratory health, which can be critical for drivers with respiratory conditions (Shahrestani et al., 2021). In the context of diseases like COVID-19, where respiratory complications have become a widespread concern, the ability to continuously monitor lung function has taken on greater importance (Kaminsky et al., 2023). Shahrestani et al. (2021) showed that it is possible for non-contact devices to monitor pulmonary function. Wearable pulmonary testing devices offer a non-intrusive and convenient way for drivers to keep track of their respiratory health, potentially identifying early signs of deterioration or infection. This can be vital for long-haul drivers who may be exposed to varying environmental conditions and have limited access to healthcare facilities while on the road. Ultimately, these wearable devices can contribute to driver safety

and well-being by providing timely alerts and data for preemptive healthcare actions in the face of respiratory ailments.

WEARABLE DEVICES ON THE MARKET

There are various wearable devices available on the market, each targeting different user groups based on their features and functionalities. For example, the Zephyr BH3 is designed primarily for athletes, as it excels in tracking movements and jumps, making it highly suitable for sports and performance monitoring (Nepi et al., 2016). In contrast, consumer watches like the Apple Watch Series 8 are tailored for general consumers, fitness enthusiasts, and health-conscious individuals, offering a wide range of features that cater to everyday health and fitness needs (White et al., 2024).

Furthermore, devices like the Empatica EmbracePlus are more suitable for healthcare providers and researchers (Kapustynska et al., 2024). This is due to the device's detailed and meticulous monitoring capabilities, which include a high sampling rate that allows more comprehensive statistical analysis and the calculation of various physiological parameters. This makes the Empatica EmbracePlus particularly valuable for medical and research applications, where precise and extensive data collection is essential.

Table 1 presents various wearable devices available on the market. For our research, because we needed a detailed analysis of drivers' fatigue conditions using beat-to-beat intervals, the team selected the Empatica EmbracePlus for this study. Empatica is one of very few device manufacturers using PPG to measure HRV from the wrist (Hinde et al., 2021). The watches by Empatica have been used widely in the research domain (Hu et al., 2024; Milstein et al., 2020; Ronca et al., 2023; Rukasha et al., 2020).

Table 1. Features of various watches and wearables available in the market. The devices marked in gray are smartwatches. Oura Ring 3 is a health tracking ring, Polar H10 and Zephyr BH3 are biometric sensors wrapped in a chest strap.

	Garmin Vivosmart 5	Apple Watch Series 8	Oura Ring 3	Polar H10	Fitbit Charge 5	Garmin Venu SQ	Samsung Galaxy Watch 5	EmbracePlus	Zephyr BH3	Google Pixel Watch 2
Heart Rate	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Steps	✓	✓			✓	✓	✓	✓	✓	✓
Sleep Tracking	✓	✓	✓					✓		✓
Stress	✓	✓	✓						✓	✓
Beat-to-Beat Interval	✓			✓		✓		✓		✓
Pulse Oximeter (SpO2)	✓	✓			✓	✓	✓			✓
Respiration	✓					✓			✓	✓
VO ₂ Max	✓					✓				
EKG/ECG		✓		✓			✓			✓
Android and OS Compatible	✓	iOS Only	✓	✓	✓	✓	Android Only	✓	✓	Android Only
FDA Status								Cleared		
Battery Life	Up to 7 days	Up to 36 hours	Up to 7 days	Up to 400 hours	Up to 7 days	Up to 6 days	Up to 50 hours	Up to 48 hours	Up to 35 hours	Up to 24 hours

Wearable Selection

In the process of selecting wearable devices for our study, we initially explored multiple options, including the Polar H10, as part of our data acquisition system. While the Polar H10 offered certain advantages, such as reliable heart rate monitoring and ease of use, several challenges arose while attempting to use the Polar H10 for our research purposes. The Polar H10 provides only limited variables, such as basic heart rate information and ECG data. However, our study required a more comprehensive range of physiological parameters, including detailed HRV, EDA, skin temperature, respiration rate, and other indicators essential for assessing driver fatigue and stress. Therefore, the selection of a device capable of capturing these additional variables was necessary to meet the study's objectives.

Ultimately, the Empatica EmbracePlus emerged as the preferred choice due to its ability to provide detailed, multimodal physiological data essential for our research (Que et al., 2024;

Gullapalli et al., 2024). A key factor in its selection was the device's rigorous data privacy measures. The EmbracePlus adheres to strict data protection standards, including compliance with the General Data Protection Regulation, ensuring that all collected data are securely encrypted and transmitted (Empatica Inc., n.d.). This commitment to privacy and security was critical given the sensitive nature of the data being collected, as it was essential to maintain the trust and confidentiality of our study participants.

Additionally, the device comes with dedicated research software through the Empatica CARE Lab platform.² This platform offers tools specifically designed to help researchers visualize, sync, and analyze large amounts of data. Such tools were crucial for handling the data generated during our study and helped ensure that we managed everything accurately and efficiently. Another important factor in choosing the EmbracePlus was its ability for measuring EDA, which is an important indicator of stress. Having a certified device gave us confidence that the data we collected on stress levels would be accurate and reliable for analyzing driver safety.

Finally, the EmbracePlus was designed specifically for research purposes, unlike many consumer-grade devices. It is built to handle the precise data collection needed for scientific studies, and its comfortable design made it suitable for continuous use, helping to ensure participants would wear it throughout the study. This device has also been cleared by the Food and Drug Administration (FDA) for research applications.

² <https://www.empatica.com/platform/home/>

CHAPTER 3. STUDY DESIGN AND RECRUITMENT

This study employed a repeated measures design to gather continuous health data from up to 10 long-haul commercial motor vehicle (CMV) drivers over a 5-day period, covering all driving hours during both day and night shifts. The primary aim was to assess the feasibility of using wearable devices to analyze fatigue and stress in drivers and to understand the effects of various variables, such as sleep duration and traffic conditions, on physiological indicators of fatigue and stress. For one additional driver, we also collected data for a course of 4 weeks.

INSTITUTIONAL REVIEW BOARD APPLICATION

Our study was approved by the Virginia Tech Institutional Review Board. This approval ensured that our research protocol met ethical standards for human subjects research. The Institutional Review Board reviewed our study design, participant recruitment procedures, informed consent process, data collection methods, and plans for protecting participant privacy and confidentiality. The approved protocol allowed us to recruit up to 10 CMV drivers to wear an Empatica EmbracePlus smartwatch and answer daily questionnaires for 5 days, with one participant continuing for an additional 4 weeks. This design enabled us to collect physiological data and self-reported information to examine stress and fatigue levels in long-haul truck drivers.

PARTICIPANTS AND RECRUITMENT

The participants in this study were long-haul drivers from the New River Valley and Roanoke areas in Virginia. The recruitment was managed by the Volunteer Coordination Group at the Virginia Tech Transportation Institute (VTTI). To ensure the selection of appropriate participants for our study, a comprehensive screening process was conducted. Participants had to be 21 years or older, possess a valid Class A commercial driver's license, and preferably hold a valid medical card. Full-time commercial truck drivers operating full-size tractor-trailers and driving long distances were preferred, especially those who drive 40 or more hours a week.

Participants were required to return to the local New River Valley/Roanoke area every 7 to 10 days for equipment returns and to participate for 5 workdays within a 10-day period. They had to be comfortable using smartphones, tablets, or computers, as the study involved daily online surveys. Willingness to wear a smartwatch for a minimum of 15 hours a day and to carry an additional mobile device was essential. Those with allergies to silicone, polycarbonate, or stainless steel were excluded due to the smartwatch materials.

We sought to recruit a balance of different body types, exercise habits, and smartwatch usage to ensure diverse participation. Additionally, participants were asked about their gender and ethnicity to further ensure a diverse and inclusive sample pool. The screening ensured that selected participants met the study's requirements and were capable of complying with the study protocols, thereby contributing to the reliability and validity of the research outcomes.

After screening, the participants were scheduled for in-person intake at VTTI. After they were enrolled, each participant was provided with an Empatica EmbracePlus smartwatch to be worn on the wrist, specifically positioned one or two finger-widths from the wrist bone. The smartwatch collected various types of biological data, including EDA, skin temperature, blood volume pulse, systolic peaks, steps taken, gyroscope data, and accelerometer data.

Participants continued their normal long-haul driving routes for work while wearing the smartwatch. No additional tasks were required from them beyond wearing the device. Researchers personally set up the device for each participant, provided usage instructions, and retrieved the device upon the completion of the study. The wearable device was Bluetooth-enabled, and data were transmitted directly to the Empatica server through the Empatica CARE Lab application installed on a project mobile phone with an internet connection via Verizon. The device, cleared by the FDA and widely used for research, presented no known health hazards.

DATA COLLECTION

Participants wore the Empatica EmbracePlus smartwatch for a minimum of 15 hours every day over the 5-day study period. Furthermore, one participant wore a device for the course of 4 weeks. The smartwatch continuously collected physiological data, which was securely synced to the Empatica server through the project mobile device. Throughout the study, questionnaires were administered to gather information on participants' demographics, daily driving experiences, diet, stress levels, and their experience wearing the device. These questionnaires were administered before, during, and after the participation period to provide comprehensive insights into the drivers' conditions and experiences.

This study aimed to explore the utility of wearable technology in monitoring and understanding the factors affecting fatigue and stress in long-haul CMV drivers. By collecting and analyzing a range of physiological and self-reported data, researchers hoped to gain valuable insights into the drivers' health and well-being and to identify potential strategies for mitigating fatigue and stress in this population.

PRE-ENROLLMENT QUESTIONS

To understand the health and habits of long-haul truck drivers, a comprehensive questionnaire was administered during pre-participation meetings before the start of data collection. This questionnaire aimed to gather detailed information about the drivers' age, sex, body weight, height, exercise routines, access to healthy food during trips, sleep quality, diabetes status, smartwatch or wearable usage, and coping mechanisms for stress during long drives.

Specific questions included inquiries about the frequency and intensity of their exercise routines, the availability and accessibility of healthy food options on the road, and the quality of sleep during trip days. Additionally, the questionnaire sought to understand the drivers' awareness of their diabetic status and, if applicable, their habits in monitoring blood glucose levels and taking medication. It also explored the participants' use of smartwatches or wearable devices for health monitoring, listening habits to music or podcasts during travels, and methods employed to manage stress while driving long distances.

We expected this thorough assessment to provide valuable insights into the lifestyle and health challenges for long-haul truck drivers, which would contribute to a better understanding of their specific needs and the development of targeted interventions to improve their overall well-being and safety on the road. The full pre-enrollment questions appear in Appendix A.

DAILY QUESTIONNAIRES

The daily questionnaires were implemented to gather comprehensive data on various aspects of the participants' daily driving experiences and overall well-being. The questionnaires were designed to be completed the same day that the participants finished their driving shift. The purpose of these questionnaires was to cover multiple aspects. First, the questions were designed to capture the subjective stress levels of the drivers, providing insights into their psychological state during and after driving. Participants rated their stress on a scale from 1 to 5, which helped us quantify the stress experienced under different driving conditions.

Second, the questionnaires collected quantitative data on driving duration, number of breaks taken, start and end times of their shifts, and the general traffic conditions encountered. This information was crucial in understanding the external factors that might influence driver fatigue and stress levels. We also gathered data on visibility and weather conditions, which were rated as poor, good, or excellent. This allowed us to assess how environmental factors influenced the drivers' experiences.

Additionally, participants were asked about their diet and caffeine intake, which are important variables affecting overall health and stress levels. They rated their diet from very unhealthy to very healthy and reported their consumption of caffeinated and non-caffeinated beverages. Safety-critical events they encountered and any heavy lifting they performed were also documented to understand the physical demands and potential safety risks associated with their workday. Finally, the questionnaires included questions about the study devices. Participants reported whether they wore the smartwatch for the full trip and the full day and whether the mobile phone used for data synchronization was functioning properly. This ensured the reliability of the data collection process and addressed any technical issues promptly. The daily questionnaires provided to the participants appear in Appendices B and C.

DATA ACQUISITION AND PROCESSING

We collected data from drivers using the Empatica EmbracePlus device, which recorded various physiological parameters continuously throughout the drivers' shifts (see Figure 1). The recorded data were uploaded to the Empatica server, and we accessed those data via an Amazon Web Services storage platform provided by Empatica, ensuring secure and efficient data transfer. The data from the Empatica server were initially in Avro files, which we converted into the required formats, primarily CSV, for ease of data analysis. We manually selected the time frames when the drivers were wearing the watch and tagged these frames as driving and non-driving periods based on the times reported by the drivers in their daily responses. This approach ensured that the data were accurately captured, processed, and categorized, enabling precise and reliable data analysis for our study.

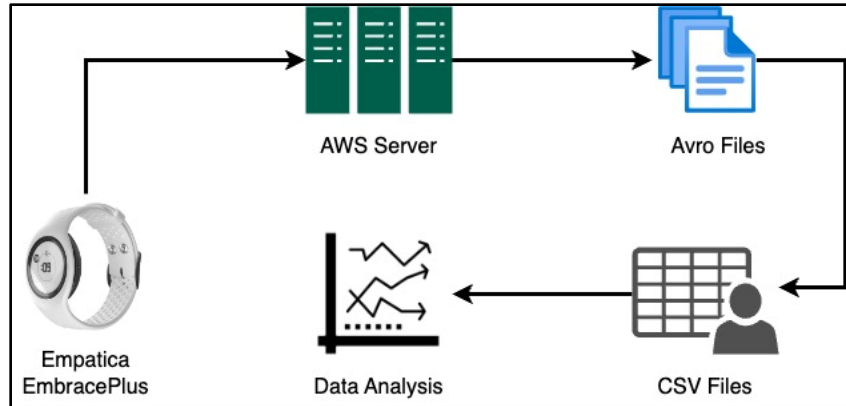


Figure 1. Diagram. Flow diagram for data acquisition from the EmbracePlus smartwatch.

EXIT SURVEYS

The exit surveys were conducted to gather feedback from participants regarding their experience using the Empatica EmbracePlus smartwatch. These surveys aimed to identify any discomfort, technical issues, or other challenges faced by the participants during the study. Participants were asked if the smartwatch caused any discomfort, irritation, or inconvenience during use. This question was crucial to determine the wearable device’s impact on the participants’ physical comfort over the 5-day period. Additionally, participants were queried about whether wearing the smartwatch affected their driving behavior or focus in any noticeable way, allowing us to assess if the device had any unintended influence on their driving performance.

The survey also sought information on any technical issues or challenges participants encountered, such as connectivity problems or discomfort while using the smartwatch. Participants described the most difficult aspects of using the smartwatch, providing insights into potential areas for improvement in future studies or device designs.

Lastly, an open-ended question allowed participants to share any additional feedback about their experience wearing the smartwatch. These qualitative data were valuable for understanding the participants’ overall experience and identifying any other factors that might not have been covered by the structured questions. By analyzing the responses from the exit surveys, we aimed to gain a comprehensive understanding of the user experience and address any issues that could affect the reliability of the data collected or the feasibility of using such devices in future studies. The exit survey is provided in Appendix D.

PARTICIPANT DEMOGRAPHIC STATISTICS

A total of 11 participants were initially enrolled in the study. However, due to data collection issues for one participant, their data were excluded from the final analysis. Among the 10 remaining participants, one individual took part in the study for an initial duration of 1 week and then participated again for an extended period of 4 weeks. Below, we present the statistics for the demographics and health-related characteristics of the study participants, including their age, sex, body weight, height, exercise routines, access to healthy food during trips, sleep quality, diabetes status, smartwatch or wearable usage, and coping mechanisms for stress during long drives.

General Characteristics

In our study, there were eight male and two female participants, with general characteristics shown in Figure 2. Additionally, the participants reported a range of ages, body weights, and heights. The age of the participants spanned from 33 to 63 years, with a mode of 46 years, a median of 50 years, and an average age of 49 years. Similarly, height measurements ranged from 162.6 to 190.5 cm, with a mode of 177.8 cm. The median height was 180.32 cm, and the average height was 180.59 cm. In terms of body weight, participants weighed between 170 and 360 lb, with the most common weight (mode) being 205 lb. The median body weight was 215 lb, and the average weight was 235 lb.

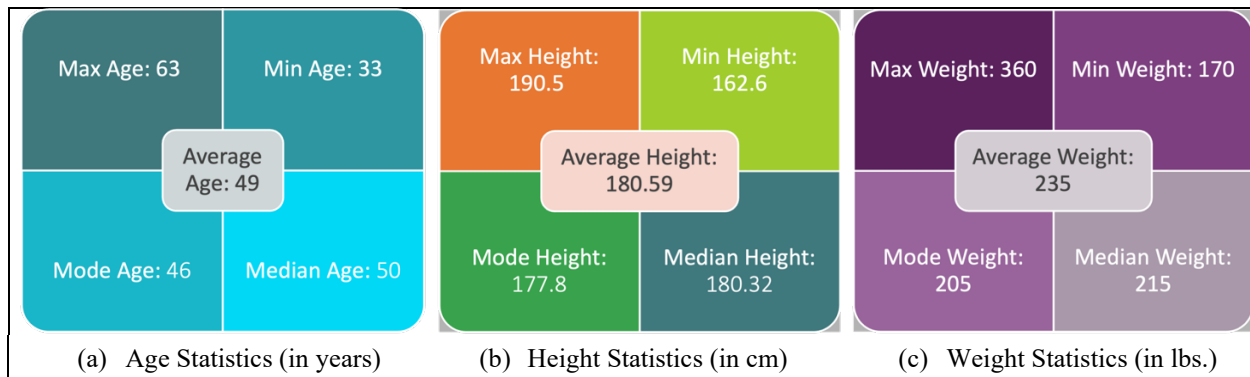


Figure 2. Infographic. Statistics of general characteristics of the participants.

Health and Lifestyle Factors

Exercise Routines

On average, participants engaged in light exercise 3.3 days a week and moderate exercise 0.8 days a week. This indicates that, while the majority of their physical activity was of low intensity, some participants did incorporate moderate exercise into their routines.

Diabetes Status

In terms of diabetes status, one participant was identified as borderline diabetic, while the remaining participants were non-diabetic.

Access to Healthy Food

Participants' access to healthy food during their trips varied. The overall responses by the participants are as follows:

- **Seven participants** selected "I found a reasonable number of healthy food options during my trip. Most restaurants had a salad or grilled chicken option," indicating moderate accessibility to healthy food (Score 4).
- **One participant** selected "There were only a few places with healthy options, and they were far away. I had to drive miles to find a salad," highlighting limited accessibility to healthy food (Score 2).

- **One participant** selected “I had no trouble finding healthy food; it was readily available. Almost every restaurant had a healthy choice on the menu,” showing excellent accessibility to healthy food (Score 5).
- **One participant** did not carry lunch and had their meal before driving and another meal after the end of their night shift. This participant did not eat food during their shift, which is a different eating pattern compared to others.

It is also interesting to note that most of the drivers carried their own lunch.

Sleep Quality

Participants reported varying sleep quality during their trips:

- **Three participants** selected “Yes, I sleep extremely well during my trip days. The new environment doesn’t affect my sleep quality, and I feel refreshed each morning,” indicating excellent sleep quality (Score 5).
- **Five participants** selected “I sleep fairly well during my trip days. The quality of sleep is good, despite the change in location and routine,” showing good sleep quality (Score 4).
- **One participant** selected “I have an average sleep during my trip days. While it isn’t great, it also isn’t terrible. The new surroundings take some getting used to,” reflecting average sleep quality (Score 3).
- **One participant** selected “I struggle with sleep during my trip days, and it isn’t very restful. The change in environment disrupts my usual sleep routine,” indicating poor sleep quality (Score 2).

These responses suggest that while most participants managed to maintain good sleep quality during their trips, a few experienced challenges due to changes in environment and routine. Additionally, we also asked participants how their sleep quality for non-trip days were. All participants reported that they usually have a good sleep.

Smartwatch and Wearable Usage

In our study, four participants reported regularly using a smartwatch in the past, while six participants had not used a smartwatch. The participant who participated in the extended 4-week study was familiar with using a smartwatch. Among the four participants who used smartwatches regularly, their opinions on the effectiveness of these devices in monitoring their health varied:

- **One participant** rated the effectiveness as a Score 3, indicating that the smartwatch helps to some extent in monitoring health.
- **One participant** rated it as a Score 1, expressing that they do not think it helps in monitoring their health.
- **Two participants** rated it as a Score 4, suggesting that they find the smartwatch quite effective in monitoring their health.

These responses indicate a mixed perception of the usefulness of smartwatches for health monitoring among the truck drivers, with some finding significant benefits and others perceiving minimal or no impact.

Music or Podcast Use While Driving

All 10 participants reported listening to music or podcasts while traveling as a way to cope with stress. Among these, eight participants listened to music, four tuned into the radio, three preferred podcasts, and one participant listened to preaching. It is important to note that participants often engaged in multiple types of listening activities to help manage the stress of long drives.

Coping Mechanisms for the Stress

In our study involving 10 truck drivers, participants reported utilizing a variety of strategies to manage stress while on the road. It was common for drivers to employ multiple coping mechanisms. The most prevalent strategies were listening to music and talking on the phone, each cited by five participants as their preferred methods for alleviating stress. Additionally, some drivers engaged with content that provided distraction or entertainment, such as listening to podcasts or preaching, each mentioned by one participant. Another participant found that simply relaxing was an effective way to cope with stress. In terms of managing stressful situations, two participants indicated that letting things go helped them manage stress levels. Moreover, cursing and smoking were each mentioned by one participant as methods used to cope with the demands and pressures of long-haul driving. Figure 3 shows the word cloud of the common ways to cope with stress among the participants. The larger size of the words represents more common coping strategies.



Figure 3. Diagram. Word cloud of common ways to cope stress among participants.

CHAPTER 4. SURVEY RESPONSE AND ANALYSIS

As mentioned above, participants were required to complete various daily and pre-participation questionnaires to capture a comprehensive range of data regarding their health, well-being, and experiences while driving. The pre-participation questionnaires collected baseline information about the participants' demographics, health status, lifestyle habits, and attitudes towards wearable technology, while the daily questionnaires provided ongoing insights into their daily experiences, including stress levels, traffic conditions, visibility, diet quality, caffeinated and non-caffeinated beverage intake, and the number of breaks taken during driving shifts.

This chapter presents a detailed analysis of the survey responses. We explore the data collected to identify patterns and trends in participants' stress levels, dietary habits, hydration practices, driving conditions, and overall experiences throughout the study period. By examining these responses, we gained valuable insights into the factors influencing the well-being of long-haul drivers and identified potential strategies for managing stress and fatigue in this population. The analysis will cover each variable individually, providing a summary of the findings for each aspect of the participants' experiences, followed by a discussion of the implications of these findings for long-haul driver health and safety. The summary of the responses of individual participants is provided in Table 2. Similarly, the box plot and participant response statistics for survey variables are provided in Figure 4 and Table 3, respectively.

Table 2. Summary of individual participant responses.

Participants	No. of Days (n)	Statistical Variables	Number of Breaks Taken	No. of Hours Driven	Stress Rating	General Traffic Conditions	Visibility	Quality of Food	No. of Non-caffeinated Drinks	No. of Caffeinated Drinks
CAS001	5	Mean $\pm$ S.D.	1.2 $\pm$ 0.4	6.3 $\pm$ 2.1	1.6 $\pm$ 0.5	1.4 $\pm$ 0.5	2.6 $\pm$ 0.5	2.6 $\pm$ 0.5	2.0 $\pm$ 0.0	4.4 $\pm$ 1.1
		Range	[1, 2]	[5.0, 10.0]	[4, 5]	[1, 2]	[2, 3]	[2, 3]	[2, 2]	[3, 6]
CAS002	7	Mean $\pm$ S.D.	2.7 $\pm$ 0.8	10.9 $\pm$ 0.8	1.9 $\pm$ 0.9	1.4 $\pm$ 0.5	2.4 $\pm$ 1.0	4.0 $\pm$ 0.0	0.1 $\pm$ 0.4	0.3 $\pm$ 0.8
		Range	[2, 4]	[10.25, 12.5]	[3, 5]	[1, 2]	[1, 3]	[4, 4]	[0, 1]	[0, 2]
CAS003	6	Mean $\pm$ S.D.	0.2 $\pm$ 0.4	8.5 $\pm$ 1.0	1.7 $\pm$ 0.8	1.2 $\pm$ 0.4	2.2 $\pm$ 0.4	2.8 $\pm$ 0.4	0.0 $\pm$ 0.0	1.5 $\pm$ 0.5
		Range	[0, 1]	[7.0, 10.0]	[3, 5]	[1, 2]	[2, 3]	[2, 3]	[0, 0]	[1, 2]
CAS004	6	Mean $\pm$ S.D.	1.0 $\pm$ 0.0	7.5 $\pm$ 0.0	1.8 $\pm$ 1.2	1.2 $\pm$ 0.4	1.8 $\pm$ 0.4	2.8 $\pm$ 0.4	0.0 $\pm$ 0.0	3.0 $\pm$ 0.0
		Range	[1, 1]	[7.5, 7.5]	[2, 5]	[1, 2]	[1, 2]	[2, 3]	[0, 0]	[3, 3]
CAS005	5	Mean $\pm$ S.D.	2.2 $\pm$ 1.3	9.2 $\pm$ 0.4	1.6 $\pm$ 0.5	1.2 $\pm$ 0.4	2.8 $\pm$ 0.4	3.2 $\pm$ 0.4	0.4 $\pm$ 0.5	2.4 $\pm$ 0.9
		Range	[0, 3]	[9.0, 10.0]	[4, 5]	[1, 2]	[2, 3]	[3, 4]	[0, 1]	[1, 3]
CAS006	5	Mean $\pm$ S.D.	0.2 $\pm$ 0.4	6.1 $\pm$ 1.0	1.8 $\pm$ 0.8	1.0 $\pm$ 0.0	2.4 $\pm$ 0.5	2.0 $\pm$ 1.2	0.0 $\pm$ 0.0	1.4 $\pm$ 0.9
		Range	[0, 1]	[5.0, 7.5]	[3, 5]	[1, 1]	[2, 3]	[1, 4]	[0, 0]	[1, 3]
CAS007	6	Mean $\pm$ S.D.	1.2 $\pm$ 0.4	9.1 $\pm$ 0.5	1.5 $\pm$ 0.5	2.0 $\pm$ 0.0	1.8 $\pm$ 0.4	3.0 $\pm$ 0.0	0.2 $\pm$ 0.4	2.2 $\pm$ 0.8
		Range	[1, 2]	[8.5, 9.5]	[4, 5]	[2, 2]	[1, 2]	[3, 3]	[0, 1]	[1, 3]
CAS009	5	Mean $\pm$ S.D.	1.0 $\pm$ 0.0	8.3 $\pm$ 1.3	1.2 $\pm$ 0.4	2.0 $\pm$ 0.7	2.8 $\pm$ 0.4	4.4 $\pm$ 0.5	0.0 $\pm$ 0.0	1.0 $\pm$ 0.0
		Range	[1, 1]	[7.0, 10.0]	[4, 5]	[1, 3]	[2, 3]	[4, 5]	[0, 0]	[1, 1]
CAS010	4	Mean $\pm$ S.D.	1.0 $\pm$ 0.8	8.1 $\pm$ 1.4	1.5 $\pm$ 0.6	1.8 $\pm$ 0.5	2.5 $\pm$ 0.6	4.2 $\pm$ 0.5	0.2 $\pm$ 0.5	0.5 $\pm$ 0.6
		Range	[0, 2]	[6.5, 10.0]	[4, 5]	[1, 2]	[2, 3]	[4, 5]	[0, 1]	[0, 1]
CAS011	5	Mean $\pm$ S.D.	1.0 $\pm$ 0.0	8.6 $\pm$ 0.1	2.6 $\pm$ 0.9	2.2 $\pm$ 0.8	1.6 $\pm$ 0.9	3.2 $\pm$ 0.4	0.2 $\pm$ 0.4	4.4 $\pm$ 1.1
		Range	[1, 1]	[8.4, 8.7]	[2, 4]	[1, 3]	[1, 3]	[3, 4]	[0, 1]	[3, 6]

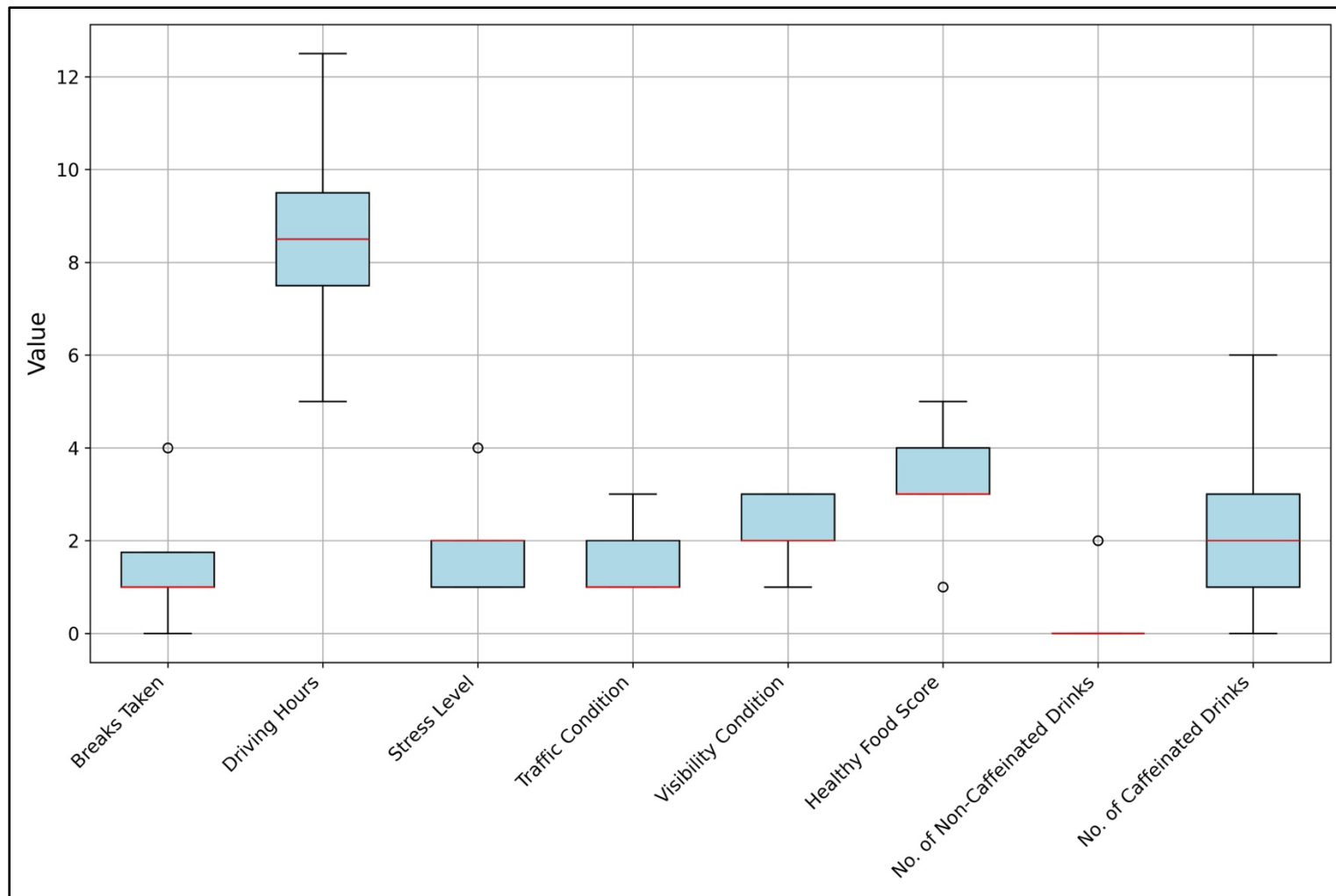


Figure 4. Box plot. Survey variables for all participant responses.

Table 3. Statistics of survey variables for all participant responses.

Variables	Number of Breaks Taken	No. of Hours Driven	Stress Rating	General Traffic Conditions	Visibility	Quality of Food	No. of Non-caffeinated Drinks	No. of Caffeinated Drinks
Mean ($\bar{x}$)	1.20	8.36	1.72	1.52	2.28	3.22	0.30	2.07
Std. (s)	0.96	1.67	0.79	0.61	0.69	0.86	0.63	1.55
Minimum	0	5	1	1	1	1	0	0
25%	1	7.5	1	1	2	3	0	1
50%	1	8.5	1	1	2	3	0	2
75%	1.75	9.5	2	2	3	4	0	3
Maximum	4	12.5	3	3	3	5	2	6

ANALYSIS OF PARTICIPANT RESPONSES

Number of Breaks Taken

As shown in Table 2, participants reported the number of breaks they took during their driving shifts, which varied across the group. The distribution of breaks taken was as follows: 11 instances of no breaks, 29 instances of one break, seven instances of two breaks, six instances of three breaks, and one instance of four breaks.

Overall, the most common pattern was taking one break, followed by no breaks. A smaller number of participants took two or more breaks, with three and four breaks being relatively rare. This suggests that while some drivers preferred to drive without interruptions, most took at least one break during their shifts to rest and recuperate. The statistics also show somewhat common break patterns of participants.

Number of Hours Driven

As shown in Table 2, the average number of hours driven by participants was 8.36 hours, with a standard deviation of 1.67 hours. The minimum number of hours driven was 5, while the maximum was 12.5 hours. The distribution of driving hours is further detailed by the quartiles: the 25th percentile (25%) was 7.5 hours, indicating that 25% of the driving instances were at or below this duration. The median (50th percentile) was 8.5 hours, showing that half of the driving instances were 8.5 hours or less. The 75th percentile (75%) was 9.5 hours, meaning that 75% of the driving instances were at or below this duration. This distribution suggests that most driving shifts were between 7.5 and 9.5 hours, with occasional longer shifts reaching up to 12.5 hours.

Stress Ratings

Participants rated their stress levels during or after driving on a scale from 1 to 5, and Score 5 was not reported by any participants. As shown in Table 2, the distribution of stress ratings was as follows: 24 instances of very little to no stress (Score 1), 23 instances of mild stress (Score 2), five instances of moderate stress (Score 3), and two instances of quite stressed (Score 4).

Overall, the majority of participants experienced very little to no stress or mild stress during or after driving. Moderate stress was less common, and only a few participants reported feeling quite stressed. This indicates that most driving experiences were manageable in terms of stress levels, with only occasional instances of higher stress.

Traffic Condition During Driving

Participants rated the traffic conditions they experienced during their driving shifts. As shown in Table 2, the distribution of their ratings was as follows: 29 instances of easy traffic (Score 1), 22 instances of moderately challenging traffic (Score 2), and three instances of very challenging traffic (Score 3).

Overall, the majority of participants reported experiencing easy traffic conditions, indicating a smooth commute without major delays. Moderately challenging traffic was also common, with some delays and congestion, but manageable. Very challenging traffic conditions were rare.

Overall Visibility

The participants rated the visibility and weather conditions they encountered during their shifts. As shown in Table 2, the distribution of their ratings was as follows: seven instances of poor visibility (Score 1), 25 instances of good visibility (Score 2), and 22 instances of excellent visibility (Score 3).

Overall, good visibility conditions were the most frequently reported, followed by excellent visibility. Poor visibility was less commonly experienced, indicating that most driving conditions were favorable regarding weather and visibility.

Quality of Food Consumed During the Shift

The participants rated the quality of their diet during shifts, which revealed significant variation. As shown in Table 2, there were two instances of very unhealthy diets (Score 1), six instances of unhealthy diets (Score 2), 27 instances of neutral diets (Score 3), 16 instances of healthy diets (Score 4), and three instances of very healthy diets (Score 5).

Overall, the majority of participants reported a neutral diet, with a significant number also indicating healthy food choices. Very unhealthy and very healthy diets were less commonly reported.

Number of Non-caffeinated Drinks

The consumption of non-caffeinated drinks among participants varied. There were 43 instances of no drinks, six instances of one drink, and five instances of two drinks. Some participants, such as CAS001, consistently consumed two non-caffeinated drinks on all five occasions. CAS002, on the other hand, had no drinks on six occasions and one drink on one occasion. Participants like CAS003 and CAS004 consistently did not consume any non-caffeinated drinks on all six recorded occasions. CAS005 showed some variation, with no drinks on three occasions and one drink on two occasions. Similarly, CAS006 and CAS009 consistently had no drinks on five occasions. CAS007 had no drinks on five occasions and one drink on one occasion, while CAS010 and CAS011 also primarily did not consume any non-caffeinated drinks, with a few instances of one drink.

Number of Caffeinated Drinks

The caffeine consumption among participants varied significantly. The distribution of caffeine intake is as follows: 16 instances of one drink, 14 instances of three drinks, eight instances each of two drinks and no drinks, four instances of four drinks, and two instances each of five and six drinks. Individually, some participants like CAS001 and CAS011 showed mixed patterns with varying high intake, while others like CAS002 and CAS009 consistently avoided caffeine. Participants such as CAS003, CAS005, CAS006, and CAS007 had moderate and varied intake, reflecting diverse habits in managing their alertness during long shifts.

Safety-critical Events While Driving

Only one safety-critical event was reported while driving. Out of 54 trips, having just one safety-critical event indicates a low frequency of such incidents, suggesting that driving conditions were generally safe for the participants.

Heavy Lifting as Part of the Job

Most participants did not engage in heavy lifting as a part of their job. Only nine out of 54 trips involved heavy lifting. At the participant level, only four out of 10 participants reported heavy lifting. One participant performed heavy lifting on all five days, while two others did so on one day each, and one participant did heavy lifting on two days. This indicates that heavy lifting was a relatively uncommon task among the participants.

RELATIONSHIP ANALYSIS OF RETROSPECTIVE STRESS AND REPORTED VARIABLES

To understand the relationship between retrospective stress levels and various reported driving conditions, a series of linear mixed effects models were constructed. These models used each participant as a random effect and included independent variables from the self-report questionnaires as fixed effects. The independent variables considered in the analysis were traffic conditions, visibility and weather conditions, heavy lifting performed, and safety-critical events encountered. The results of these models are illustrated in Figure 5.

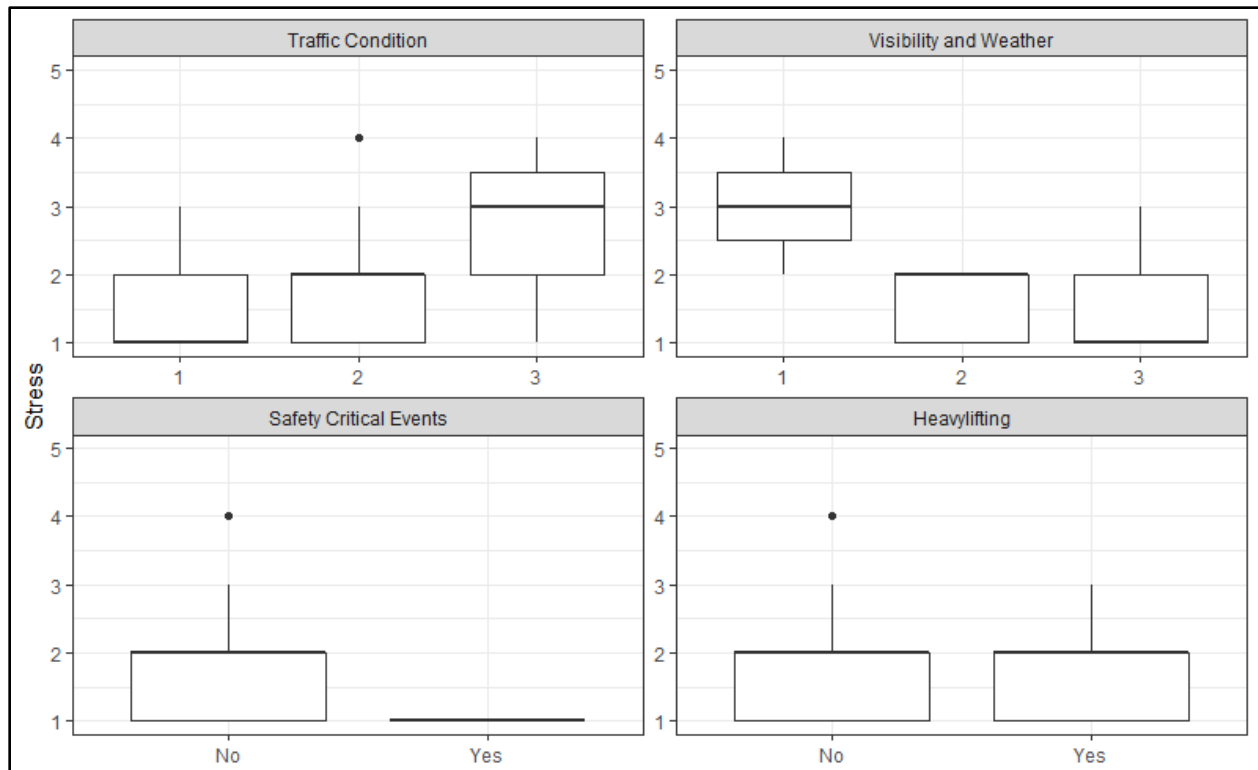


Figure 5. Box plots. Independent variables from self-report questionnaire on retrospective stress level.

The log-likelihood ratio test revealed significant correlations between retrospective stress levels and two key variables: traffic conditions, $X^2(2) = 8.70, p = .012$, partial $\eta^2 = 0.16$, and visibility, $X^2(2) = 18.41, p < .001$, partial $\eta^2 = 0.21$. Post hoc comparisons using Tukey's test showed that participants who reported traffic conditions as very challenging (Score 3) experienced significantly higher retrospective stress levels compared to those who reported easy driving conditions (Score 1), with $t(58.8) = -2.45, p = .045$.

In addition, post hoc comparisons with Tukey's test indicated that drivers who reported visibility of 2 or 3 also reported a lower retrospective stress level compared to drivers who reported visibility of 1 (reporting visibility of 2 to 1: $t(57.4) = 4.03, p < .001$; reporting visibility of 3 to 1: $t(54) = 4.09, p < .001$).

DISCUSSION

Previous research has established that traffic conditions are associated with driving stress levels in passenger vehicles, as reported by Hennessy and Wiesenthal (1997), Neighbors et al. (2002), and Hill and Boyle (2007). Our study extends this understanding by examining how traffic conditions impact long-haul commercial vehicle drivers' perception of stress retrospectively. We found that long-haul drivers who experienced more challenging traffic conditions reported higher stress levels at the end of the day compared to those who encountered easier traffic. This finding underscores the significant impact that traffic conditions can have on the stress levels of commercial drivers, consistent with what has been observed in passenger vehicle drivers.

In addition, our study revealed that visibility and weather conditions also affect long-haul commercial drivers' retrospective stress levels. Hill and Boyle (2007) suggested that adverse weather conditions may increase stress due to a perceived lack of vehicle control. However, they found that limited visibility alone did not significantly elevate stress levels to the same degree. Our study differs from Hill and Boyle's findings, particularly in the context of long-haul commercial drivers. We hypothesize that poor visibility, often associated with adverse weather conditions, contributes significantly to increased stress levels in this group. This difference suggests that visibility and weather conditions might be intertwined factors for long-haul drivers, and further research is needed to clarify whether these drivers perceive them as distinct stressors.

Moreover, we explored whether performing heavy lifting during the day or encountering safety-critical events influenced drivers' retrospective stress levels. Our findings indicated no significant association between these factors and stress levels. However, the data on safety-critical events were limited, with most responses indicating that such events did not occur. This skewed distribution suggests that more comprehensive data collection is necessary to draw firmer conclusions about the role of heavy lifting and safety-critical events in influencing stress among long-haul drivers.

In summary, our study provides valuable insights into the factors that contribute to stress in long-haul commercial vehicle drivers, highlighting the importance of traffic conditions and visibility. Further research, particularly with more extensive data on safety-critical events and heavy lifting, is needed to deepen our understanding of these influences and to develop effective strategies for managing driver stress.

CHAPTER 5. ANALYSIS OF PHYSIOLOGICAL SIGNALS

PARTICIPANT HEART RATE ANALYSIS

In terms of heart rate analysis for participants, we identified distinct patterns where heart rates increased with elevated stress levels. The exploratory data analysis indicates a trend of rising heart rates correlating with longer trip durations. This increase in heart rate is often attributed to a higher cognitive load associated with prolonged driving and complex driving conditions.

As seen in the graphs in Figure 6, participants' heart rates were lower during sleep periods, represented by the green lines, with average rates around 75 to 80 beats per minute. However, during driving periods, marked by the blue lines, heart rates consistently increased, reflecting heightened physiological arousal or stress. Notably, there is a visible upward trend in heart rate over time while driving, suggesting that sustained driving activity leads to accumulated stress and fatigue. Additionally, specific actions or moments, such as reaching a destination or taking a break, were associated with fluctuations in heart rate. For example, the heart rate remained elevated during driving periods and gradually reduced when breaks were taken, indicating recovery from the exertion and stress of driving.

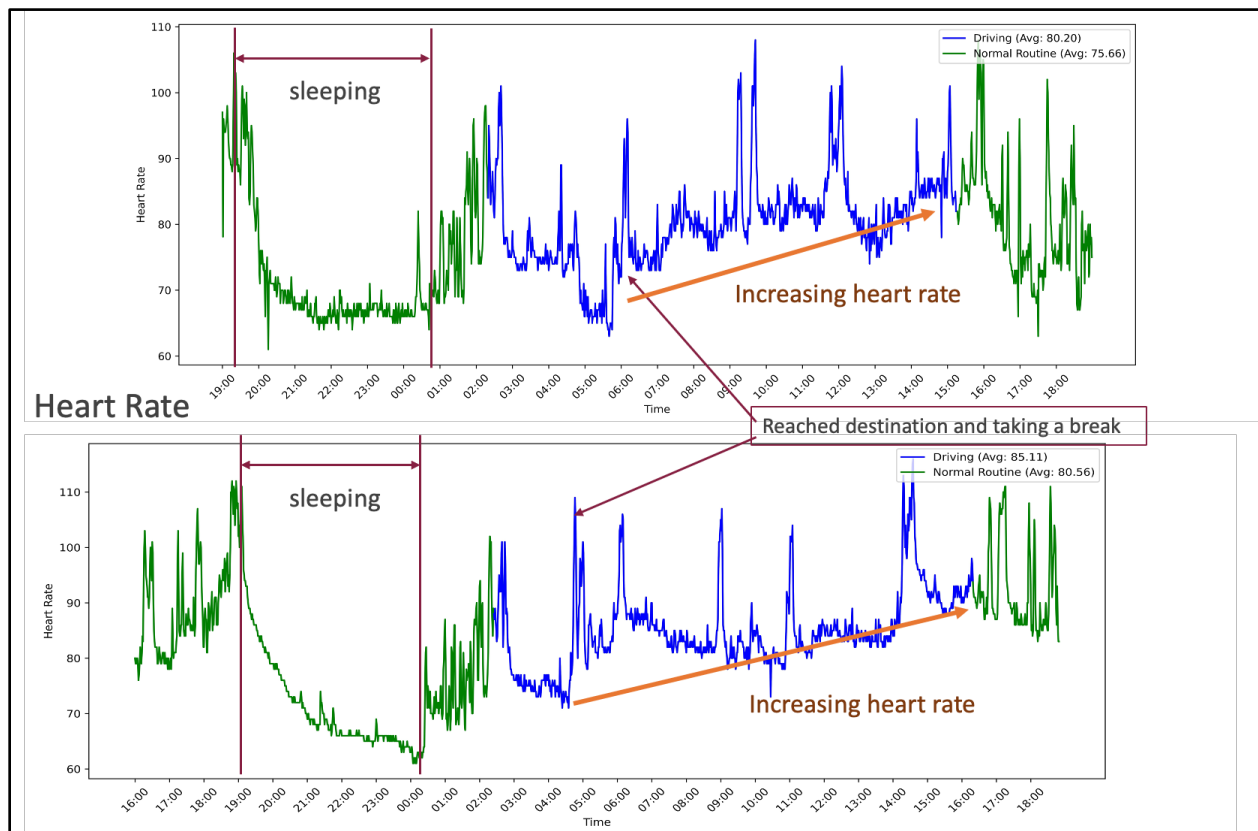


Figure 6. Graphs. An example of increasing heart rate indicating higher cognitive load.

Heart Rate Slope Analysis Across Time Intervals

We further explored the relationship between heart rate changes and stress by examining the slopes of heart rate data for participants over 30-minute intervals. The slope represents the rate of change in heart rate over time, with positive slopes indicating an increase in heart rate, which may correspond to rising stress levels or cognitive load. Conversely, negative slopes represent a decrease in heart rate, potentially indicating relaxation or recovery periods.

To compute these slopes, we analyzed heart rate data by dividing it into 30-minute segments for each participant. For each segment, as shown in Figure 7, the slope of heart rate over time was calculated and recorded, along with the corresponding time intervals. The analysis covered multiple participants, involving loading heart rate data, filtering between specific timestamps, and determining slopes for each time window.

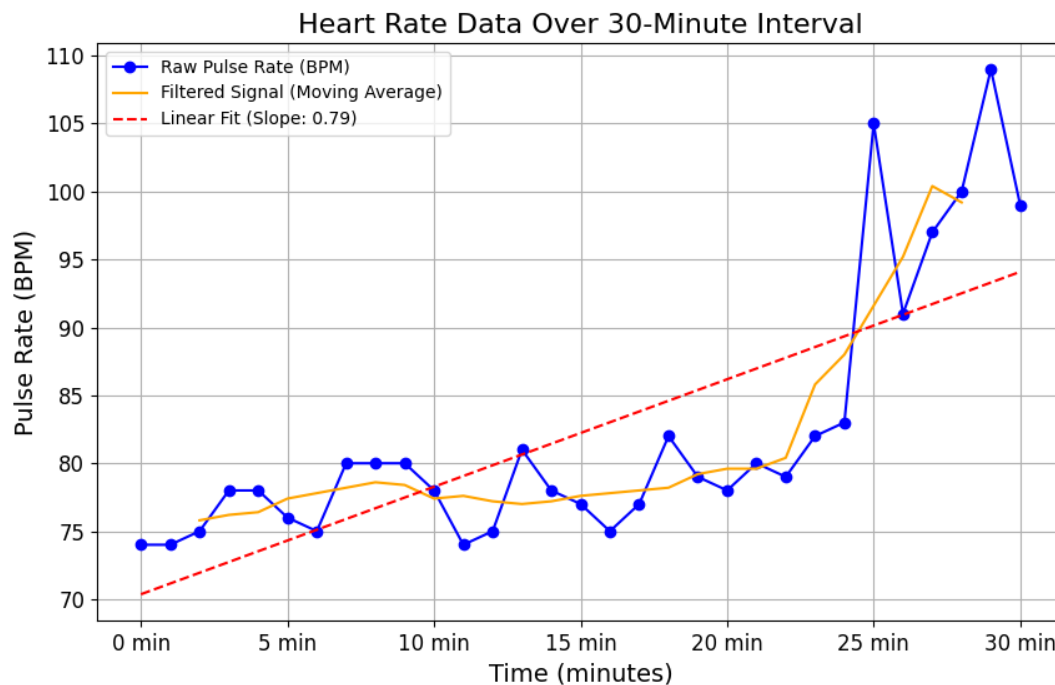


Figure 7. Graphs. Heart rate slope calculation for a 30-minute interval. The plot displays the raw heart rate signal (blue line), the filtered signal to remove noise (orange line), and the fitted line (red) used to calculate the slope.

The slope plot as shown in Figure 8 illustrates the variation in heart rate slopes for all participants across different times of the day. Each point on the graph represents the slope of heart rate over a 30-minute interval, with time represented on the x -axis and slope values on the y -axis. This plot shows a mixture of positive and negative slopes throughout the day, highlighting the dynamic nature of heart rate changes in response to different driving conditions and activities.

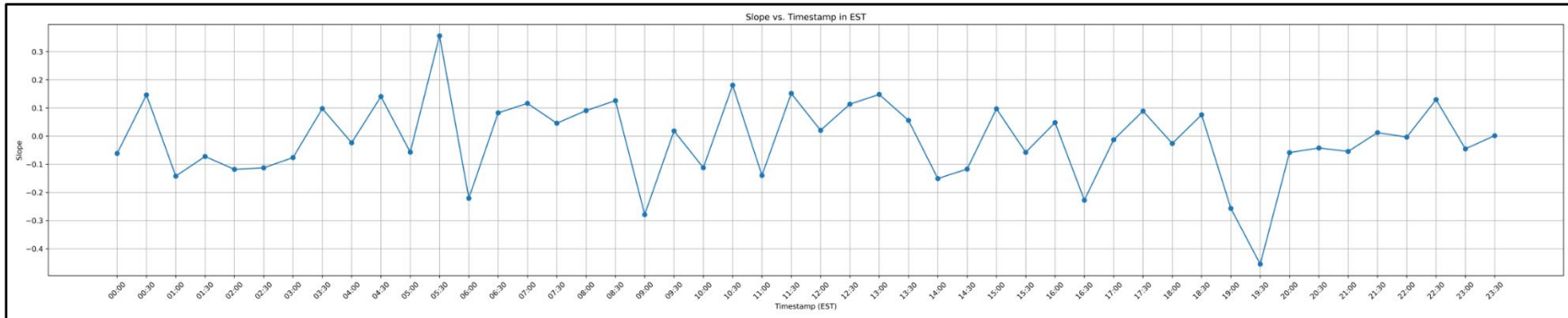


Figure 8. Graph. Variation in heart rate slopes over time for all participants with respect to time of the day.

Positive slopes, which indicate increasing heart rates, are observed at various times, particularly during early morning and midday periods. These likely correspond to times of increased cognitive load or stress, such as active driving or dealing with challenging traffic conditions. Negative slopes, representing decreasing heart rates, are seen intermittently, especially during the late afternoon and early evening, suggesting periods when drivers may be taking breaks or experiencing recovery.

These fluctuations in slopes throughout the day suggest that heart rate dynamics are influenced by multiple factors, including the time of day and driving conditions. The comprehensive view provided by this plot highlights critical periods that may require closer monitoring for stress management and well-being interventions among long-haul drivers.

In addition to the study of slope changes with respect to the time of day, we also examined how the average slope of heart rate changes correlates with the total number of hours driven. This analysis aimed to explore whether prolonged driving hours are associated with distinct patterns of physiological stress, as reflected in heart rate dynamics. While slope changes over the course of a day provided insights into moment-to-moment variations in stress levels due to factors such as traffic conditions or breaks, examining the slope with respect to total driving hours offers a broader perspective on how cumulative driving time might affect stress and fatigue.

As shown in Figure 9, the average slope of heart rate changes fluctuates significantly across the total hours driven. The plot reveals a mix of positive and negative slopes, suggesting that heart rate does not consistently increase or decrease over time. There are notable drops in the slope around the sixth and 12th hours of driving, which may correspond to rest breaks or moments of reduced stress. Conversely, more positive slopes toward the end of the driving period suggest an overall trend of increasing heart rate, potentially due to accumulated fatigue or heightened stress from prolonged driving.

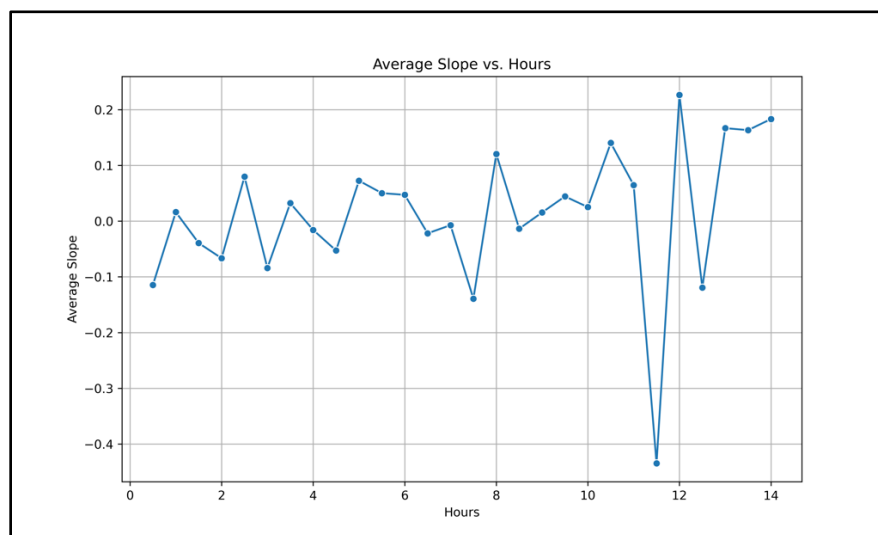


Figure 9. Graph. Average slope of heart rate changes in relation to total hours driven.

These findings indicate that heart rate dynamics are complex and do not follow a simple linear pattern in relation to driving duration. Instead, they appear to be influenced by a range of factors, including the timing of rest periods, driving conditions, and individual stress resilience. However, further research is necessary to better understand these relationships and to identify specific factors that contribute to variations in heart rate and stress levels among long-haul drivers. Future studies should explore these dynamics in greater detail to inform effective interventions aimed at managing stress and promoting the well-being and safety of drivers over extended periods.

Correlation of Number of Positive Heart Rate Slopes vs. Stress

We analyzed the correlation between the number of positive heart rate slopes calculated over 30-minute intervals and self-reported stress levels and found a correlation coefficient of 0.208, as shown in Figure 10. This weak positive correlation suggests a slight association between the two

variables: as the number of positive heart rate slopes increases, there is a marginal tendency for self-reported stress levels to rise.

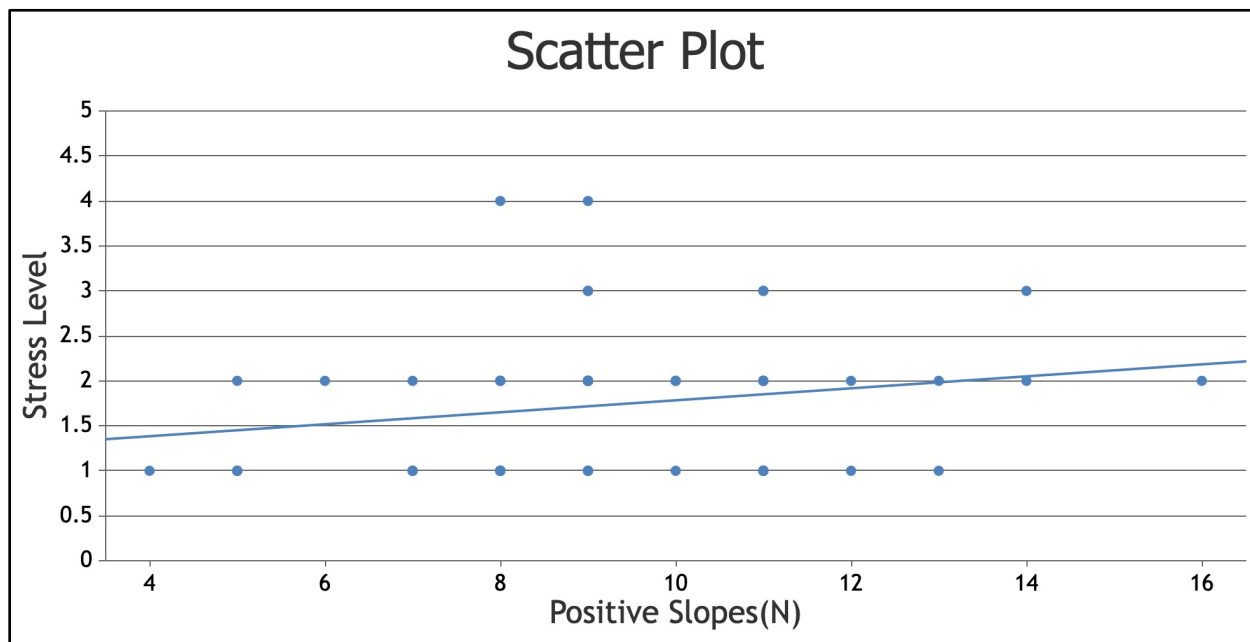


Figure 10. Graph. Correlation between the number of positive heart rate slopes calculated over 30-minute intervals and self-reported stress levels.

The positive heart rate slope represents periods where the heart rate increases over a 30-minute window, potentially indicating moments of heightened cognitive load, stress, or physical exertion. A correlation of 0.208 implies there may or may not be a link between these intervals of rising heart rate and perceived stress. This result suggests that other factors likely influence the drivers' stress levels beyond the physiological changes reflected in heart rate alone.

Several factors could explain this lack of correlation. For one, individual differences in stress perception and physiological responses play a significant role; not all drivers may experience stress similarly when their heart rate increases. For some participants, an increased number of positive heart rate slopes might directly correspond to stressful driving situations, such as heavy traffic or adverse weather conditions. For others, similar heart rate changes could be influenced by non-stress-related factors like physical activity, caffeine consumption, or other personal health conditions.

Additionally, stress is a multifaceted phenomenon influenced by a range of external and internal factors, including psychological state, environmental conditions, and individual coping mechanisms. This complexity may account for the relatively low correlation, suggesting that while heart rate slopes over 30-minute intervals provide some indication of stress, they are not sufficient on their own to fully capture the drivers' stress levels.

To better understand the relationship between physiological responses and perceived stress, future research should consider integrating more comprehensive data, including real-time contextual information about driving conditions and individual differences in stress resilience.

This approach would help to refine the understanding of how heart rate dynamics relate to stress and could lead to more effective monitoring and management strategies for long-haul drivers.

Analysis of Heart Rate Increase from Baseline

In addition to the analysis of heart rate slopes, we further examined how heart rates deviated from a defined baseline for each participant. The baseline was established as the lower 10th percentile of the individual's heart rate, representing their typical low heart rate state, likely corresponding to periods of minimal activity or relaxation. The percentage increase from this baseline was calculated to understand how different states—specifically “rest” and “driving”—influenced heart rate changes.

The box plot in Figure 11 illustrates the distribution of these percentage increases for all participants, separated by state (rest in blue and driving in orange). This visual representation reveals clear patterns in heart rate changes associated with different activities, providing insights into the physiological stress responses of each participant.

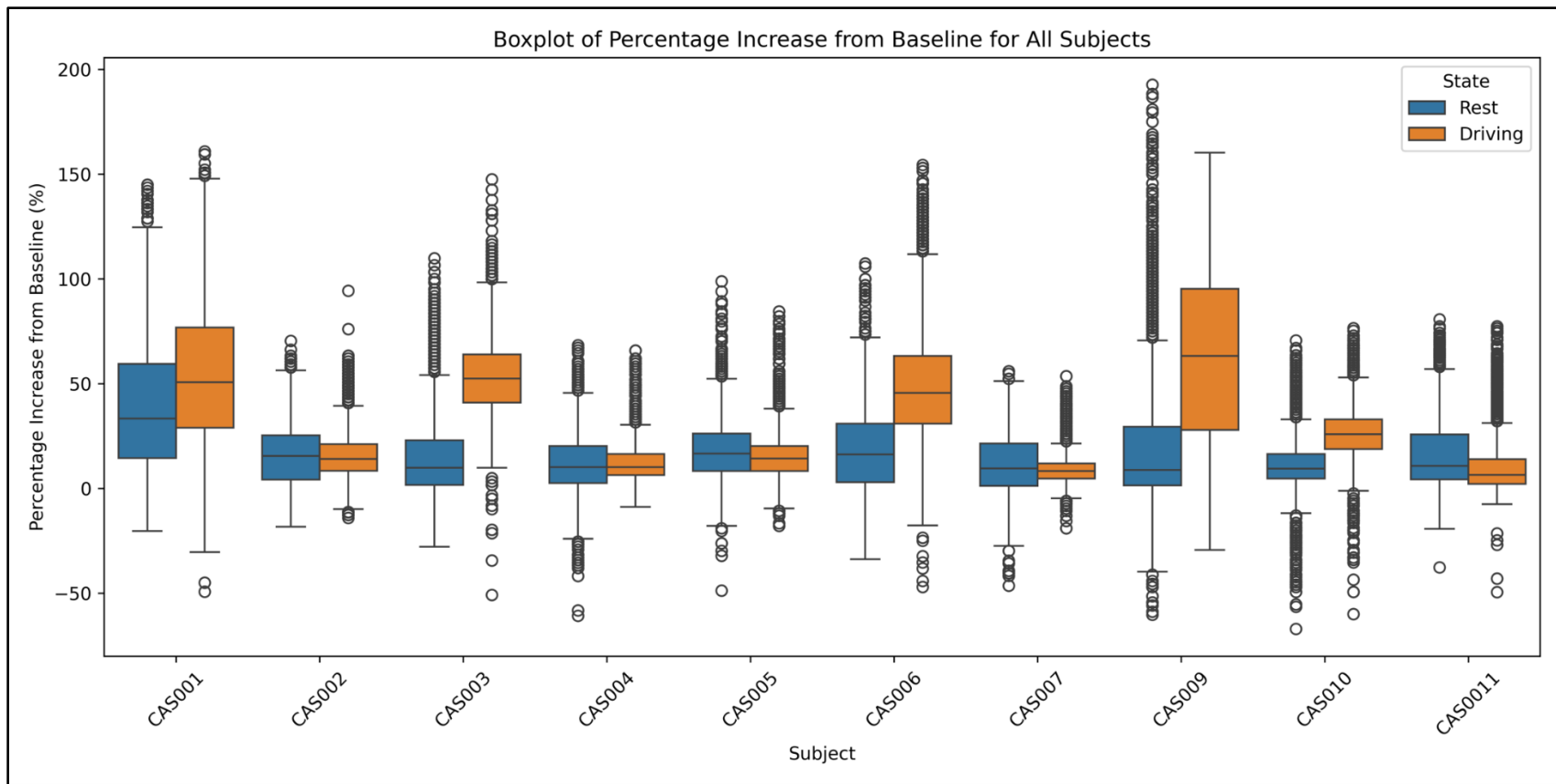


Figure 11. Box plot. Percentage increase in heart rate from baseline for all subjects during rest and driving states.

Among half of participants, there is a noticeable difference between the rest and driving states. The driving state generally shows a higher median percentage increase and a wider IQR compared to the rest state. This suggests that driving, especially over long distances, is associated with increased physiological arousal, as reflected in elevated heart rates above the baseline. The broader IQR in the driving state indicates greater variability in heart rate responses, which could result from varying driving conditions, road environments, or individual stress responses to prolonged cognitive load.

Specific participants, such as CAS001, CAS003, CAS006, and CAS009, displayed significant differences between their heart rates during resting and driving periods. For example, CAS003 showed a considerable elevation in median heart rate during driving, along with a longer upper whisker and numerous high-value outliers. This pattern suggests that the participant experienced frequent or intense episodes of increased heart rate while driving, potentially due to high stress or cognitive demands associated with the task. Similarly, CAS001, CAS006, and CAS009 exhibited smaller increases in heart rate percentages during driving, indicating a notable physiological response to driving stress or exertion.

Conversely, some participants, like CAS002, CAS004, CAS005, CAS007, and CAS010, showed relatively smaller differences in heart rate increases between the two states. For these participants, the distributions for resting and driving states are more overlapping, with similar medians and IQRs, suggesting less variation in heart rate response. This could imply that these individuals experienced lower levels of stress while driving or were more adept at managing stress under such conditions. For instance, CAS004's nearly overlapping distributions for both states may reflect effective stress management techniques or a reduced sensitivity to stressors.

Figure 11 also highlights the presence of outliers in both states for most participants, indicating instances where heart rate increases were significantly above or below the typical range. These outliers could result from specific, transient events or conditions that provoked an acute physiological response. For example, in the driving state, outliers may correspond to stressful situations such as navigating through heavy traffic, sudden weather changes, or emergency maneuvers. Outliers in the resting state might be related to unexpected disturbances, physical activities during rest breaks, or other external stimuli.

Overall, the analysis of heart rate increases from the baseline demonstrates that driving generally leads to more significant and more variable heart rate elevations compared to resting. However, there is substantial individual variability in these physiological responses. Some drivers exhibited pronounced heart rate increases, indicating greater stress or cognitive load, while others maintained relatively stable heart rates, suggesting better resilience or coping mechanisms.

PARTICIPANT SKIN TEMPERATURE ANALYSIS

We also analyzed the skin temperature of participants to assess potential variations between the rest and driving states. The box plot in Figure 12 depicts the distribution of skin temperatures for all subjects, with data separated into rest (blue) and driving (orange) states. This analysis aimed to understand whether skin temperature, as a physiological measure, could provide insights into the stress levels or comfort of drivers under different conditions.

For some participants, the median skin temperature during driving was similar to or slightly higher than during the rest state. However, these differences were inconsistent across participants, with some showing higher temperatures while driving and others displaying no significant change or even lower temperatures. This inconsistency suggests that skin temperature may not be a reliable indicator of driving stress.

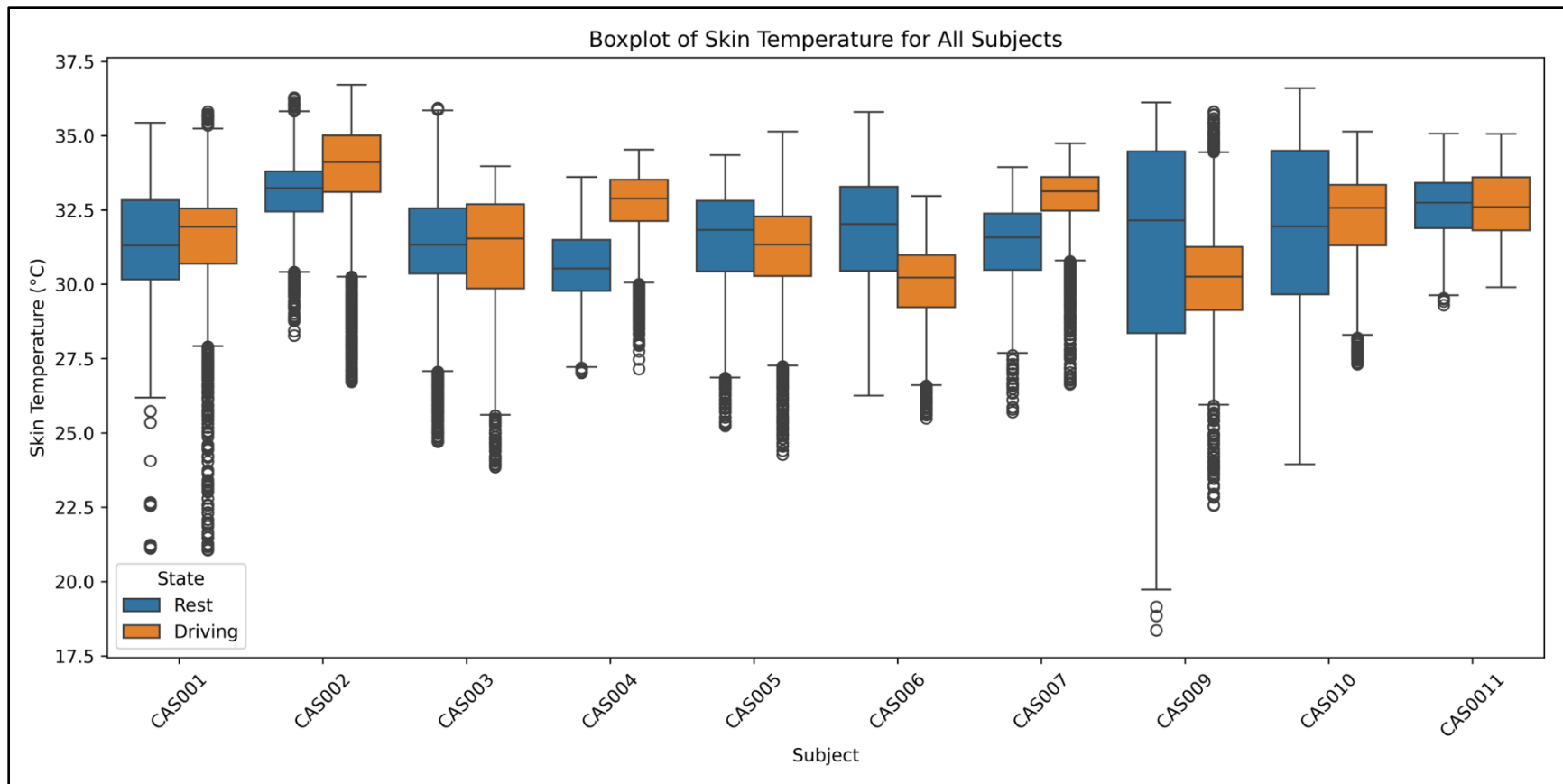


Figure 12. Box plot. Skin temperature of all subjects.

The variability in skin temperature, indicated by the IQR, also differs among participants. Some participants, such as CAS009 and CAS010, displayed a wider range of temperatures, especially during driving. This could reflect individual differences in how skin temperature responds to stress or other environmental factors while driving. In contrast, participants like CAS002, CAS004, and CAS007 had narrower ranges, indicating more stable skin temperatures regardless of the state.

Notably, there are several outliers present in both the rest and driving states, indicating instances where skin temperatures deviated significantly from the typical range. These outliers could be attributed to a variety of factors, such as variations in ambient temperature, individual thermoregulatory responses, or specific situational factors (like cabin temperature) affecting each participant differently.

Overall, while Figure 12 suggests that there may be some variation in skin temperatures between the rest and driving states, the findings are somewhat inconclusive. The differences were not uniformly observed across all participants, and the presence of outliers and variability makes it difficult to draw definitive conclusions about the relationship between skin temperature and driving conditions.

Further research is needed to better understand how skin temperature might relate to physiological stress or comfort levels in long-haul drivers. Future studies could involve more controlled conditions, larger sample sizes, or additional physiological measures to provide a clearer understanding of the role of skin temperature in monitoring driver well-being.

PARTICIPANT EDA ANALYSIS

We also analyzed the EDA of participants to assess physiological arousal levels and cognitive load during extended driving periods. EDA is a measure of the skin's electrical conductance, which varies with sweat gland activity and is influenced by factors such as stress, emotional arousal, and cognitive workload. By examining EDA, we aimed to understand how the cognitive demands of long-haul driving affect the physiological state of drivers over time.

The graph presented in Figure 13 illustrates the EDA readings of a participant over a 12-hour driving schedule. The plot is divided into two segments: driving (represented by the blue line) and normal routine or resting periods (represented by the green line). The x -axis shows time, while the y -axis indicates EDA levels in microsiemens (μS). The overall pattern reveals a steady increase in EDA during the driving period, which suggests a gradual rise in cognitive load and stress levels as the participant continued driving.

Notably, the EDA levels display a consistent upward trend throughout the driving hours, indicating that the participant's physiological arousal increased progressively during prolonged driving (Figure 13). This trend suggests accumulating mental fatigue or stress as the drive extended. Additionally, several sharp spikes in EDA are observed, particularly during the early morning hours, which may correspond to periods of intense cognitive demand or sudden, unexpected events requiring heightened attention and quick decision-making. These spikes could be attributed to challenging driving conditions, traffic congestion, sudden maneuvers, or other stress-inducing factors the participant encountered on the road.

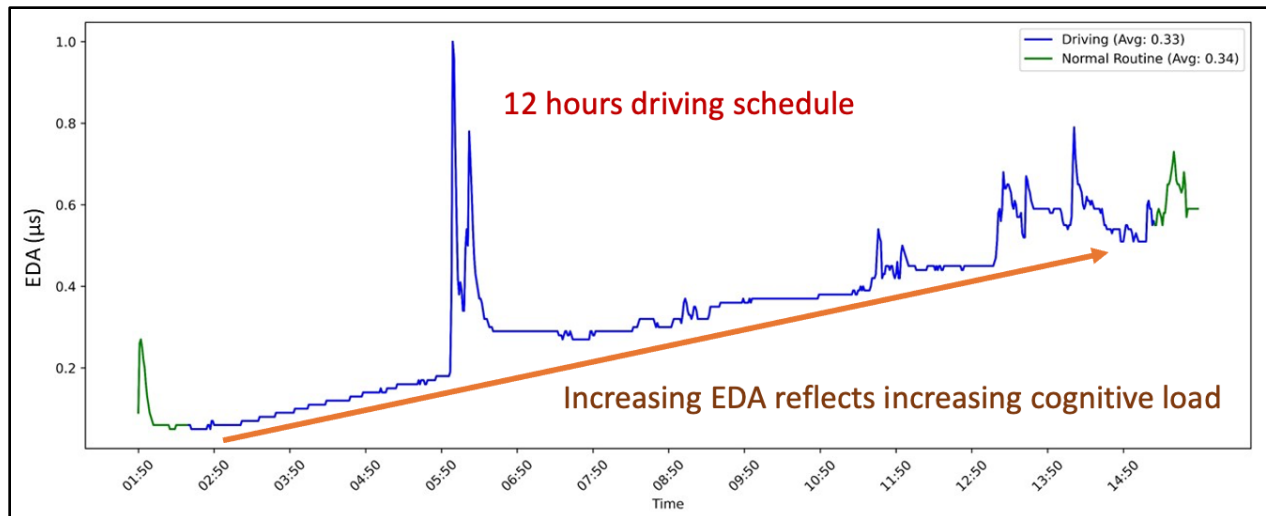


Figure 13. Graph. EDA of a participant over a 12-hour driving schedule.

When comparing EDA levels during the driving state to those during the normal routine/rest, it is evident that the driving state is associated with more fluctuations and increases in EDA. As shown in Figure 13, towards the end of the 12-hour driving schedule, the EDA levels continue to show an upward trend, reflecting sustained or even increasing cognitive load. This pattern indicates that the participant's physiological arousal remains elevated, possibly due to accumulated fatigue or ongoing stress from prolonged driving hours. The persistence of high EDA levels at the end of the driving period highlights the cumulative impact of extended driving on physiological stress responses.

Overall, the analysis of EDA data suggests that long-haul driving is associated with increased cognitive load and stress, as reflected in rising EDA levels over time. The presence of sharp EDA spikes further emphasizes moments of high demand or stress during the drive. These findings underscore the importance of understanding and managing the cognitive demands placed on drivers to maintain their well-being and safety on the road.

Further research is needed to explore the specific factors contributing to increased EDA during driving, such as the nature of driving tasks, road conditions, traffic, and individual driver characteristics. Additionally, analyzing EDA responses during rest periods could provide valuable insights into the recovery process. By comparing EDA slopes during driving and rest periods, we could determine whether breaks effectively reduce physiological arousal and cognitive load. This analysis would further substantiate the argument that scheduled rest periods are crucial for mitigating stress, enhancing driver performance, and ensuring overall safety during long-haul journeys. Understanding these dynamics can guide the development of targeted strategies and interventions aimed at promoting driver well-being and road safety.

DISCUSSION

Our data collection procedure did not involve minute-by-minute annotation of specific events or real-time recording of occurrences during the driving sessions. Instead, it relied solely on post-trip self-reports from participants. This method presents potential limitations, as participants may

have forgotten certain details or only recalled specific moments that were particularly memorable or stressful, which could skew the accuracy of the data. The reliance on retrospective self-reports may lead to biased interpretations of the factors contributing to physiological changes, such as spikes in EDA, as participants are less likely to remember all relevant details comprehensively.

To gain a more accurate and truthful understanding of the relationship between driving conditions and physiological responses, future studies should incorporate more detailed and real-time data collection methods. Continuous monitoring of environmental and contextual variables, such as traffic density, road conditions, and specific driving maneuvers, along with real-time self-reports or automated event logging, would provide a more granular understanding of the stressors faced by drivers. Such an approach could improve the reliability of the data and lead to more precise insights into the factors that contribute to increased cognitive load and stress among long-haul drivers.

CHAPTER 6. CONCLUSIONS

In conclusion, this study provides valuable insights into the physiological responses and stress levels of long-haul truck drivers, contributing to a growing body of research aimed at improving road safety and driver well-being. The findings show the complex interplay of various factors—including heart rate, skin temperature, EDA, and driving conditions—influencing the physical and cognitive states of drivers over extended periods. Our research highlights the need for comprehensive, real-time monitoring methods to better understand and mitigate the risks associated with fatigue and stress in long-haul drivers.

The analysis of heart rate data revealed that prolonged driving often leads to increased heart rates, indicating elevated physiological arousal and cognitive load. This trend was particularly evident during extended driving sessions, where sustained increases in heart rate suggested accumulating fatigue and stress. Further, our examination of heart rate slopes over 30-minute intervals showed dynamic fluctuations throughout the day, corresponding to varying driving conditions, activities, and periods of rest.

Our study also explored the heart rate increases from a defined baseline, comparing the rest and driving states for each participant. The findings indicated that driving generally led to more significant and variable heart rate elevations compared to rest. However, there was substantial individual variability in these physiological responses, with some drivers exhibiting pronounced heart rate increases, likely due to greater stress or cognitive load, while others maintained relatively stable heart rates, suggesting better resilience or coping mechanisms.

In analyzing skin temperature data, we found that while some participants experienced higher median skin temperatures during driving, the differences between rest and driving states were not consistent across all participants. This variability suggests that skin temperature alone may not be a definitive indicator of stress or comfort levels, and further research is needed to explore its potential as a reliable metric for monitoring driver well-being.

The study of EDA revealed that long-haul driving is associated with increased cognitive load and stress, as reflected in rising EDA levels over time. The presence of sharp EDA spikes during the early morning hours and throughout the driving period indicated moments of high demand or stress, likely due to challenging driving conditions or sudden events requiring quick decision-making. These findings underscore the importance of understanding and managing the cognitive demands placed on drivers to maintain their well-being and safety on the road.

The study's methodology, which relied on post-trip self-reports, presented some limitations. The absence of minute-by-minute event annotations or real-time recording of occurrences may have led to biased interpretations of the factors contributing to physiological changes. Additionally, this study primarily focused on single-factor analyses to understand the impact of individual physiological metrics, such as heart rate, EDA, and skin temperature, on stress and fatigue. While these analyses provided important insights, they do not account for the interplay between multiple factors that may simultaneously influence driver stress and fatigue. For example, relationships between spikes in EDA and heart rate changes or the combined effects of environmental conditions, such as traffic and visibility, remain unexplored.

Future research should adopt multi-factor analysis to examine these interactions and confirm the findings from this study. By analyzing multiple variables together—such as the correlation between EDA spikes and heart rate increases, or the influence of traffic density and visibility on physiological stress—researchers can gain a more comprehensive understanding of the factors influencing driver stress and fatigue. Such an approach would help identify key stressors more effectively and inform the development of tailored interventions to improve driver well-being and safety.

Additionally, the study's sample size was limited, and the data collection focused on a relatively small group of participants over shorter period of time. Expanding the study to include a larger and more diverse sample of drivers would enhance the generalizability of the findings and allow a more comprehensive understanding of the factors influencing stress and fatigue among long-haul drivers.

The insights gained from this study have several practical implications for improving road safety and promoting driver well-being. The findings suggest that real-time monitoring of physiological metrics, such as heart rate, EDA, and skin temperature, using wearable technologies could be a valuable tool for detecting early signs of fatigue and stress among long-haul drivers. Such monitoring could prompt timely interventions, such as recommending rest breaks or adjusting driving schedules, to prevent accidents and enhance overall road safety. Moreover, understanding the factors contributing to stress and fatigue, including driving conditions, traffic, and individual resilience, can inform the development of targeted strategies to support drivers' well-being.

In conclusion, this study contributes to a deeper understanding of the physiological responses and stress levels of long-haul truck drivers, highlighting the complex interplay of factors that impact their well-being and safety on the road. While the findings underscore the importance of real-time monitoring and intervention strategies, they also point to the need for further research to develop more effective tools and approaches for managing driver fatigue and stress. By advancing our knowledge in this area, we can work towards enhancing the health, safety, and performance of long-haul drivers, ultimately contributing to safer roads for all.

APPENDIX A. PRE-ENROLLMENT QUESTIONNAIRE

Participants were asked these questions during our meeting with them to hand over the study materials and device up to 3 days before their first day of data collection.

1. What is your current age in years? _____
2. What is your sex? M or F _____
3. What is your current body weight? _____
4. What is your height? _____
5. How many days a week do you engage in exercise (walking, lifting weights)? _____
6. Out of the days in a week that you engage in exercise, how many days would you consider:
Light (The light exercise could be walking slowly e.g., shopping, walking around the office, preparing food)
Moderate (The moderate exercise could be sweeping the floor, walking briskly, slow dancing, vacuuming, washing windows, or shooting a basketball)
Intense (Intense exercise could be running (5 mph >), swimming, shoveling, soccer, jumping rope, or carrying heavy loads)
Light: _____ Day(s)
Moderate: _____ Day(s)
Intense: _____ Day(s)
7. Do you think you have access to healthy food during your trips? (1 - 5)
____ Score 1- I couldn't find any healthy food options anywhere I went, just fast food and sugary snacks.
____ Score 2- There were only a few places with healthy options, and they were far away. I had to drive miles to find a salad.
____ Score 3- I had to search for healthy food, but I found a couple of options like a small local cafe with salads and a grocery store with some fresh produce.
____ Score 4- I found a reasonable number of healthy food options during my trip. Most restaurants had a salad or grilled chicken option.

____ *Score 5* - I had no trouble finding healthy food; it was readily available. Almost every restaurant had a healthy choice on the menu.

8. Do you sleep well during your trip days?

____ *Score 1* - No, I have significant difficulty sleeping during my trip days. The unfamiliar surroundings and discomfort affect my sleep negatively.

____ *Score 2* - I struggle with sleep during my trip days, and it isn't very restful. The change in environment disrupts my usual sleep routine.

____ *Score 3* - I have an average sleep during my trip days. While it isn't great, it also isn't terrible. The new surroundings take some getting used to.

____ *Score 4* - I sleep fairly well during my trip days. The quality of sleep is good, despite the change in location and routine.

____ *Score 5* - Yes, I sleep extremely well during my trip days. The new environment doesn't affect my sleep quality, and I feel refreshed each morning.

9. Do you believe that you get enough sleep on non-trip days? (Yes/No) _____

10. Do you know if you are diabetic/ prediabetic/ not diabetic/unsure _____

11. If diabetic, do you regularly measure your blood glucose level? (Yes/No)

11b. If diabetic, do you take any regular medication? (Yes/No) _____

12. Do you use a smartwatch/ wearable regularly? (Yes/No)

13. If you do wear a smartwatch/wearable regularly, do you think it helps you monitor your health? (1-5)

____ *Score 1* - I don't think it helps me monitor my health.

____ *Score 2* - its impact on monitoring my health is minimal.

____ *Score 3* - it helps me monitor my health to some extent.

____ *Score 4* - it's quite effective in monitoring my health.

____ *Score 5* - it's extremely helpful in monitoring my health.

13b. If yes, can you share the name and model? _____

14. Do you listen to music/podcasts during your travels? _____

15. How do you cope with stress while driving trucks for long distances? _____

APPENDIX B. DAILY QUESTIONNAIRE FOR 5-DAY DATA COLLECTION

1. How do you rate your stress today during/after driving? (1 - 5)

_____ **Score 5** - I was extremely stressed during/after driving. It was a highly stressful experience, and I felt overwhelmed.

_____ **Score 4** - I was quite stressed during/after driving. The experience was stressful, and I felt tense.

_____ **Score 3** - I felt moderately stressed during/after driving. It wasn't too bad, but I did experience some stress.

_____ **Score 2** - I experienced mild stress during/after driving. It was manageable, and I remained relatively calm.

_____ **Score 1** - I felt very little to no stress during/after driving. It was a stress-free experience, and I was relaxed.

2. How many hours did you drive today in total? _____ Hour(s)

3. How many breaks did you take? _____ Break(s)

4. What time did you start? _____

5. What time did you end your drive today? _____

6. How was the general traffic condition today?

_____ **Easy:** The traffic today was quite easy to navigate. There were no major delays, and I had a smooth commute.

_____ **Moderately Challenging:** The traffic was moderately challenging today. There were some delays and congestion, but nothing too overwhelming.

_____ **Very Challenging:** The traffic was very challenging today. I encountered significant delays, and congestion, and it was a stressful commute.

7. How was the visibility and weather condition?

_____ **Poor:** The visibility and weather conditions today were poor. It was difficult to see due to heavy rain, fog, or other adverse weather conditions.

_____ **Good:** The visibility and weather conditions today were good. There were no significant visibility issues, and the weather was clear or mildly cloudy.

_____ **Excellent:** The visibility and weather conditions today were excellent. It was a clear, sunny day with great visibility.

8. You had a healthy diet today?

____ **Score 1: Very Unhealthy** - My diet today was very unhealthy, with mostly poor food choices.

____ **Score 2: Unhealthy** - My diet today was unhealthy, with more poor choices than healthy ones.

____ **Score 3: Neutral** - My diet today was neither healthy nor unhealthy, a mix of both.

____ **Score 4: Healthy** - My diet today was healthy, with more nutritious choices than unhealthy ones.

____ **Score 5: Very Healthy** - My diet today was very healthy, with almost entirely nutritious food choices.

9. How many caffeinated beverages have you had today?

____ Cup(s) Coffee ____ Cup(s) Tea ____ Energy Drink(s) ____ Soda

10. How many non-caffeinated Energy drinks have you had today? ____

11. Did you face any safety-critical event today? (Yes/No) ____

12. Did you do any heavy lifting as part of your job today? (Yes/No) ____

The following questions will ask about your study devices.

13. Did you wear the device for the full trip today? Yes/No ____

14. Did you wear the device for the full day today (24hrs)? Yes/No ____

15. Is the phone working properly? Yes/No ____

16. Are you experiencing any problems with the phone? Yes/No ____

APPENDIX C. DAILY QUESTIONNAIRE FOR 4-WEEK DATA COLLECTION

1. How do you rate your stress today during/after driving? (1 - 5)

____ **Score 5** - I was extremely stressed during/after driving. It was a highly stressful experience, and I felt overwhelmed.

____ **Score 4** - I was quite stressed during/after driving. The experience was stressful, and I felt tense.

____ **Score 3** - I felt moderately stressed during/after driving. It wasn't too bad, but I did experience some stress.

____ **Score 2** - I experienced mild stress during/after driving. It was manageable, and I remained relatively calm.

____ **Score 1** - I felt very little to no stress during/after driving. It was a stress-free experience, and I was relaxed.

2. How many hours did you drive today in total? _____ Hour(s)

3. How many breaks did you take? _____ Break(s)

4. What time did you start? _____

5. What time did you end your drive today? _____

6. How was the general traffic condition today?

____ **Easy:** The traffic today was quite easy to navigate. There were no major delays, and I had a smooth commute.

____ **Moderately Challenging:** The traffic was moderately challenging today. There were some delays and congestion, but nothing too overwhelming.

____ **Very Challenging:** The traffic was very challenging today. I encountered significant delays, and congestion, and it was a stressful commute.

7. How was the visibility and weather condition?

____ **Poor:** The visibility and weather conditions today were poor. It was difficult to see due to heavy rain, fog, or other adverse weather conditions.

____ **Good:** The visibility and weather conditions today were good. There were no significant visibility issues, and the weather was clear or mildly cloudy.

____ **Excellent:** The visibility and weather conditions today were excellent. It was a clear, sunny day with great visibility.

8. You had a healthy diet today?

____ **Score 1: Very Unhealthy** - My diet today was very unhealthy, with mostly poor food choices.

____ **Score 2: Unhealthy** - My diet today was unhealthy, with more poor choices than healthy ones.

____ **Score 3: Neutral** - My diet today was neither healthy nor unhealthy, a mix of both.

____ **Score 4: Healthy** - My diet today was healthy, with more nutritious choices than unhealthy ones.

____ **Score 5: Very Healthy** - My diet today was very healthy, with almost entirely nutritious food choices.

9. How many caffeinated beverages have you had today?

____ Cup(s) Coffee ____ Cup(s) Tea ____ Energy Drink(s) ____ Soda

10. How many non-caffeinated Energy drinks have you had today? ____

11. Did you face any safety-critical event today? (Yes/No) ____

12. Did you do any heavy lifting as part of your job today? (Yes/No) ____

The following questions will ask about your study devices.

13. Did you wear the device for the full trip today? Yes/No ____

14. Did you wear the device for the full day today (24hrs)? Yes/No ____

15. Is the phone working properly? Yes/No ____

16. Are you experiencing any problems with the phone? Yes/No ____

17. How many hours did you exercise or engage in outdoor activities? ____ Hours

18. How many hours did you drive beyond truck driving for work? ____ Hours

19. How many hours did you spend doing household activities? It could be cooking, cleaning, taking kids to school, or any household chores. ____ Hours

20. How many hours did you spend relaxing or watching TV/Videos/Entertainment materials/News? ____ Hours

21. What time did you go to sleep today? ____

22. What time did you wake up today? ____

23. How was the quality of your sleep?

_____ Very Poor: You had significant difficulty falling asleep or staying asleep. You woke up frequently throughout the night and had trouble getting back to sleep. You woke up feeling very unrefreshed and tired, and your sleep was not restorative at all.

_____ Poor: You experienced difficulty falling asleep or had disturbances during the night that affected your sleep quality. You may have woken up several times and found it hard to fall back asleep. You woke up feeling somewhat unrefreshed and not fully rested.

_____ Average: You had a fair night's sleep. You may have experienced brief awakenings but were able to fall back asleep relatively easily. Your sleep was somewhat restorative, and you woke up feeling moderately refreshed.

_____ Good: You fell asleep within a reasonable amount of time and stayed asleep for most of the night. You may have had minor disturbances, but they didn't significantly impact your sleep quality. You woke up feeling refreshed and well-rested.

_____ Excellent: You fell asleep quickly and slept undisturbed throughout the night. Your sleep was deep and restorative, and you woke up feeling fully refreshed, energized, and ready to start the day.

APPENDIX D. EXIT SURVEY

1. Did the Empatica EmbracePlus smartwatch cause any discomfort, irritation, or inconvenience during use?
2. Did wearing the smartwatch affect your driving behavior or focus in any noticeable way? If so, please describe.
3. Were there any technical issues or challenges you encountered while using the smartwatch, such as connectivity problems or discomfort?
4. What was the most difficult aspect of using this smartwatch?
5. Is there anything else you would like to tell us about your experience wearing this smartwatch?

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