The Role of Eco-Driving and Wearable Sensors in Industry 4.0

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Abstract This study investigates the relationship between drivers' electrodermal activity (EDA) and their eco-driving behaviours through real-time monitoring. Electrodermal activity, a physiological marker of sympathetic nervous system arousal, reflects emotional and cognitive states, providing a valuable window into drivers' internal experiences. EDA and driving data were collected for 48 trips from 10 different drivers. Cluster analysis and the Pearson correlation coefficient was used to uncover potential patterns between driver EDA and their driving behaviour as measured using a driving score. The results follow the Yerkes-Dodson Law. Driving performance increase with EDA arousal, but only to a point. The investigation has implications for enhancing road safety, as it contributes to our understanding of how drivers' emotional states influence their on-road performance. Additionally, it holds promise for developing innovative in-car systems that can adapt to drivers' changing emotional states, promoting safer and more comfortable driving experiences. Ultimately, this study bridges the gap between psychophysiology and transportation, shedding light on the often-overlooked emotional aspects of driving behaviour.

Keywords Eco-driving · Industry 4.0 · Wearable sensors · Electrodermal activity

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A. Crespo Márquez et al. (eds.), *Advances in Asset Management: Strategies, Technologies, and Industry Applications*, Engineering Asset Management Review 3, https://doi.org/10.1007/978-3-031-52391-5_10

Table 1 Paper nomenclature

Variable	Definition
AccX	Acceleration forwards or braking
AccY	Acceleration side to side
AccZ	Acceleration up and down
$AccXPos_i$	The i^{th} positive acceleration recorded from the Geotab G09 device.
$AccXNeg_i$	The i^{th} negative acceleration (braking) recorded from the Geotab G09 device.
$AccYPos_i$	The i^{th} right turn force recorded from the Geotab G09 device.
$AccYNeg_i$	The i^{th} left turn force recorded from the Geotab G09 device.
Brake	The braking score.
C	A self-reported "calm" mood.
CDC	Centers for Disease Control
Driving Score	A weighted average of the speeding, acceleration, braking, right, and left cornering scores.
EDA	Electrodermal Activity – The variation of electrical characteristics of the skin due to perspiration or sweat gland activity.
E4 Sensor	The wristband, developed by Empatica, worn by drivers to record their EDA while driving. It has a sampling frequency of 4 Hz.
F	A self-reported "fatigued" mood.
G09 Device	The telematic device, developed by Geotab, used in the study to record driving data. It is plugged into the OBD II port of the drivers' personal vehicle.
GPS	Global Positioning System
H	A self-reported "happy" mood.
L_S'	Length of the trip not spent speeding.
L	Length of a trip.
Left	The left cornering score.
Max EDA	The maximum EDA.
Mean EDA	The average EDA.
Med EDA	The median EDA.
Mood 1	The self-reported mood prior to driving.
Mood 2	The self-reported mood during driving.
NAcc	The total number of recorded acceleration events.
NBrk	The total number of recorded negative acceleration (braking) events.
NLCrn	The total number of recorded left turn events.
NRCrn	The total number of recorded right turn events.
OBD II	On-Board Diagnostics II – The second generation of on-board self-diagnostic equipment.
Right	The right cornering score.
S	A self-reported "stressed" mood.
Skew EDA	The skewness of all EDA values.
SpdFreq	The number of speeding events recorded by the telematic device.
Speed	Speed score
US	United States
Sd EDA	The standard deviation of all EDA values.
μS	microSiemens – Measures of skin conductance are expressed in units of microSiemens.

1 Introduction

A study performed by the Centers for Disease Control and Prevention (CDC) compared the United States (U.S.) to 28 other high-income countries regarding road safety and found that the U.S. experienced more motor-vehicle deaths than any other country with the highest rate of motor-vehicle deaths per 100,000 population (Yellman & Sauber-Schatz, 2022). The report further states that motor vehicle injuries are the leading cause of preventable death in the world, accounting for nearly 1.3 million deaths. Aggressive driving behaviour is one of the main reasons for crash risk (Office of Traffic Safety, 2021).

The National Highway Traffic Safety Administration (NHTSA) defines aggressive driving as “the operation of a vehicle in a manner that endangers or is likely to endanger persons or property” (Stuster, 2004). Aggressive driving is solely due to human decision-making and involves following too closely, driving at excessive speeds, weaving through traffic, and running stop lights and signs. In asset management, accidents resulting from aggressive driving can lead to substantial costs, including vehicle repairs, medical expenses, legal fees, and increased insurance premiums. Reducing aggressive driving, by supporting the driver, can help mitigate these costs and protect the financial health of the fleet.

Eco-driving, defined as an energy-efficient use of vehicles through less aggressive driving style, has garnered significant interest in the literature for its reported benefits on reducing aggressive driving habits thus, potentially, increasing road safety. Since eco-driving depends on the driver making the decision to engage in an eco-driving style, it becomes imperative to comprehend the underlying factors that influence driver’s behaviour and performance.

In terms of the physiological state of the driver, fatigue is already known to impact safety since drivers’ reaction times, awareness of hazards, and ability to sustain attention all worsen (Meng et al., 2015). Driver stress has emerged as a significant concern, directly impacting safety, operational efficiency, and driver well-being. In a search of the Scopus database of “the relationship between driver’s emotional state and aggressive driving”, only five papers were found from 2006 to 2022 with no studies that investigate the relationship between emotional arousal of the driver and aggressive driving using naturalistic driving data. The objective of this study is to investigate the relationship between drivers’ emotional arousal (measured using Electrodermal Activity) and their eco-driving score.

2 Literature Review

Aggressive driving habits, such as rapid acceleration and frequent braking, consume more fuel and decrease fuel efficiency. By encouraging smoother driving behaviours, fleet managers can reduce fuel costs and environmental impact. Aggressive driving also places additional stress on vehicles, leading to increased wear and tear on components such as brakes, tires, and engines. A reduction in aggressive driving can extend the lifespan of fleet vehicles, resulting in lower maintenance and replacement costs.

Ecological driving ("Eco-Driving") is a term used to describe "a driving behavior (or a driving style) that aims at saving fuel and reducing harmful GHG emissions" (Andrieu & Pierre, 2012; Fafoutellis et al., 2020; Barkenbus, 2010). Eco-driving involves accelerating moderately, anticipating traffic flow and signals to avoid sudden starts and stops, maintaining an even driving pace, driving at or safely below the speed limit, and eliminating excessive idling (Barkenbus, 2010). The advantages of eco-driving go beyond CO_2 reductions to include reducing the cost of driving to the individual and producing tangible and well-known safety benefits (fewer accidents and traffic fatalities) (Barkenbus, 2010; Zarkadoula et al., 2007; Beusen et al., 2009). It is already established that fatigue negatively impacts driving ability (Al-Mekhlafi et al., 2020). Recent research investigates the role of emotions and personality traits in the occurrence of aggressive driving habits.

2.1 Emotion and Aggressive Driving

Three related research aspects can be identified when studying emotions in the car: (1) the effect of emotions on aggressive driving, (2) the detection of emotions using psycho-physiological sensors, and (3) in-car responses to regulate and influence driver emotions (Hassib et al., 2019). Aggressive personality types tend to engage in more aggressive driving behaviour (Beanland et al., 2014; Alavi et al., 2017).

Primary driving tasks include all necessary tasks that control the movement of the vehicle such as steering, accelerating, braking, and speeding. These primary tasks are strongly related to safe driving and can be negatively impacted by negative emotions (Hassib et al., 2019).

Affective state changes in a person are always accompanied by significant physiological responses such as blood flow, changes in heart rate, muscles, facial expressions, and voice. According to Russell's model, each affective state can be represented by two dimensions: arousal and valence (Russell, 1980). Arousal indicates the level of a person's involvement in reaction to a stimulus. Valence defines the positive or negative emotional state. The Yerkes-Dodson Law (Yerkes & Dodson, 1908) and the inverted U-shape model provide theoretical foundations for understanding the complex interplay between stress and performance. These models propose an optimal stress zone where driver performance is at its peak.

A study by Eboli et al., 2017, used a questionnaire to investigate the relationship between driving style and drivers' somatic, behavioural, and emotional conditions (Eboli et al., 2017). They found that a driver inclines toward a more cautious driving style when tired, sleepy, sick, or bored while driving. If the driver is gloomy, worried, nervous, or angry, they driver inclines towards a more aggressive driving style.

Another study by Ahmed et al., 2022, used an emotional intelligence (EI) survey and the Dula Dangerous Driving Index survey to analyse dangerous driving behaviour among 615 non-commercial US drivers (Ahmed et al., 2022). They found significant associations between dangerous driving behaviours and EI. Specifically, higher EI scores engaged in less dangerous driving behaviours, resulting in fewer crashes and fatalities.

(Britt & Garrity, 2006) asked participants to recall a recent time when they experienced three different anger-provoking events when driving. They then rated their behaviours and emotions during the event, and their attributions for why the event occurred. Hostile and blame attributions predicted aggressive behaviour and anger.

In a study by Lee and Winston, a simulation was used to induce negative emotional states in young drivers to examine the relationship between emotional states and driver reactions (Lee & Winston, 2016). Self-reported data were collected from 33 young driver participants who reported their emotional states at four time points during the protocol. These data were then matched with vehicle control behaviours based on measures derived from the simulator. The simulated traffic situations resulted in emotional fluctuations over time, with a positive correlation between the magnitude of negative emotions and the number of unsafe behaviours.

An anonymous, web-based survey of 769 college students was conducted at a large East Coast university to investigate the relationship between distress tolerance and risky and aggressive driving (Beck et al., 2014). The authors define distress tolerance as "the individual's capability to experience and endure negative emotional states". Driver participants self-reported their emotional states at four time points during the protocol. The authors found that, after controlling for age, gender, race, ethnicity, year in school, grade point average, and driving frequency, distress tolerance was significantly inversely related to reported risky driving and aggressive driving.

Asset managers must consider the delicate balance between stress-induced arousal and optimal performance, as excessively high or low stress levels can lead to suboptimal driving behaviours. High levels of stress can impair a driver's ability to focus, react quickly, and make sound decisions on the road. Stressed drivers may be more prone to accidents, endangering themselves, other road users, and the company's assets. Paschalidis et al. (Paschalidis et al., 2019) developed a car-following model that explicitly accounts for the stress level of the driver and quantifies its impact on acceleration-deceleration decisions. They found that drivers with higher levels of stress (as manifested in the physiological responses) express similar characteristics to the "aggressive" drivers used in some microsimulation tools. The ability to describe the behaviours of drivers, even before they may be consciously aware of their likely behaviours, will provide a significant advancement to the transportation infrastructure (Dehzangi & Williams, 2015).

2.2 Wearable Sensors and Telematic Devices

Industry 4.0 aims to design machines to assist humans in being more efficient. It creates cyber-physical systems, which represent tight interaction and coordination between computational and physical resources within a smart factory (Hermawati

& Lawson, 2019). Researchers have identified eight categories in which Industry 4.0 technologies can assist operators in human-cyber physical systems: (1) operators and powered exoskeletons, (2) operators and augmented reality, (3) operators and virtual reality, (4) operators and wearable trackers, (5) operators and social networks, (6) operators and collaborative robots, (7) operators and big data analytics, and (8) operators and intelligent personal assistants (Romero et al., 2016). This work shows an application of the fourth category to monitor driver stress while driving using wearable sensors, telematics, and data insights.

Stress is a dynamic process that reflects the brain's response to internal and external factors (Butler, 1993) and is defined as "a reaction from a calm state to an excited state for the purpose of preserving the integrity of the organism" (Healey & Picard, 2005). It is linked to impaired decision-making capabilities (Baddeley, 2000), decreased situational awareness, and degraded performance, which can impair driving ability. Stress is measured via cortisol levels (Hellhammer et al., 2009) or via self-reports such as the Perceived Stress Scale (PSS) (Cohen et al., 1983). These methods cannot be used to measure stress continuously for an extended period and sometimes require a person to go to a clinician or psychologist (Mishra et al., 2020).

Recent improvements in sensing capabilities and wearable sensors (E4 Empatica device) have enabled continuous detection and monitoring of stress in several conditions: controlled, semi-controlled, and free-living conditions (Gjoreski et al., 2016; Mishra et al., 2018). One study has shown student pilots to have high EDA values during highly demanding tasks (Vallès-Català et al., 2021), as highly demanding tasks put extra pressure on them. Another study used wearable sensors to measure electroencephalography/electromyography (EEG/EMG) and heart rate to evaluate driving performance while driving under stressful conditions (Hassib et al., 2019). In addition to achieving an accuracy of 78.9% for classifying valence and 68.7% for arousal, the researchers observed enhanced driving performance when ambient lighting was introduced to calm the drivers. This indicates that wearable sensors can be used to predict emotional arousal accurately.

The E4 Empatica wristband, which includes an electrodermal activity (EDA) sensor, will be used to collect the EDA values of the participants while driving. It is an innocuous device designed to acquire information in real time and continuously throughout daily activities.

The goal of this study is to investigate whether drivers drive worse when stressed. This is an observational study in which drivers wear an Empatica E4 wristband with a telematic device plugged into the On-Board Diagnostics (OBD II) port of their personal vehicle while driving. Their eco-driving performance is measured using a driving score (T. Seecharan, 2022). A survey was used to obtain the drivers' self-reported assessments of their moods. Descriptive statistics are used to search for patterns between (1) the drivers' self-reported moods and their driving scores and (2) the drivers' raw EDA and their driving scores.

2.3 Summary

Related work shows that emotions can impact driving performance. Eco-driving can potentially improve road safety by reducing hard acceleration, hard braking, and speeding. Researchers have investigated the use of physiological sensors to understand driver emotions. However, limited research investigates the relationship between EDA and driving performance and none investigate the relationship between EDA and eco-driving performance. In this work, wearable sensors are used to observe the relationship between drivers' EDA and their eco-driving performance.

3 Methodology

Analysing EDA and eco-driving involves a combination of data collection, processing, and interpretation. A general outline of the steps involved in this analysis is as follows:

3.1 Data Collection

Driving Behaviour Data: To analyse driving behaviour, data can be collected through various sources, such as vehicle telematics, GPS devices, accelerometers, or smartphone apps. The Geotab G09 device, plugged into the drivers' on-board diagnostics (OBD II) port, collected speed, acceleration, and braking patterns.

1. EDA Data: Electrodermal activity measures electrical conductance on the skin's surface, commonly known as skin conductance or galvanic skin response. The Empatica E4 device was used to collect EDA data from the drivers.
2. Data Synchronization - The EDA data and driving behaviour data must be synchronized correctly so that both datasets can be analysed in relation to each other. In the Geotab cloud, trip start and end dates along with trip lengths were recorded. These data were matched to the EDA timestamp.
3. Preprocessing: Trips less than 5 miles in length were removed, and any EDA data that were abnormally high were removed. For one driver, there was a trip in which their EDA was in the range of 30 μS. This was abnormally high for this driver and was removed from the analyses. Driving data, EDA data, and survey responses that matched in terms of trip date and duration were retained for analysis.
4. EDA Analysis – This work uses the raw EDA data in the analysis. Descriptive statistics for the EDA recorded for each trip for each driver were calculated including mean EDA, standard deviation of the EDA (sd EDA), median EDA

(Med EDA), maximum EDA value (Max EDA), and skewness of the EDA (skew EDA). The independent variable in this study was mean EDA.

5. Eco-Driving Behaviour Analysis – Eco-driving behaviour is quantified using a “driving score”. Metrics to calculate this driving score are harsh acceleration, harsh braking, sharp turns, and excessive speed. This is the dependent variable in the study.
6. Correlation and Patterns - The correlation between mean EDA and driving score was examined. Hierarchical clustering was used to create separable clusters and observe differences in mean EDA, median EDA and driving score between clusters.
7. Interpretation – The results were interpreted, and conclusions about the connection between emotional arousal (EDA) and eco-driving behaviour were drawn. The implications of the findings for improving road safety, driver behaviour, and potential interventions were considered.

3.2 Participants

This paper presents the results from ten drivers recruited from the undergraduate student population at the University of Minnesota Duluth. Drivers must hold a valid driver’s license and valid vehicle insurance to be included in the study. They were asked to record their EDA and driving data for five trips of at least five miles in length. Drivers were also asked to record their mood via a survey. Driving data were collected using the Geotab G09 telematics device plugged into the on-board diagnostics port of the drivers’ personal vehicle. The drivers wore an E4 Empatica device while driving to record their EDA data. The E4 sensor and G09 device are shown in Fig. 1.

Driving data from the G09 device were downloaded from Geotab’s cloud storage and analysed using R. The participants were also asked to complete a short survey after each driving session. The survey questions are shown below. This survey assists in matching EDA data with vehicle engine data.

The EDA from the Empatica E4 was measured with dry electrodes that detect changes in the electrical conductivity of the skin. It sampled at a frequency of 4 Hz,

Fig. 1 E4 wristband (left) and G09 telematic device (right)

and data were measured in microSiemens (μS). The Empatica E4 is a wearable sensor worn on the wrist that is used to record physiological signals. It offers two modes of recording: (1) real-time via an app or (2) locally stored data on the device. This work used the real-time mode of recording. After finishing the real-time recording, the data were transferred to Empatica Connect via a Wi-Fi internet connection. On Empatica Connect, the E4 data can be visualized, deleted, or downloaded. Empatica offers physiological signals in raw format (e.g., EDA, blood volume pulse, temperature, and movement) but offers no tools for signal analyses.

3.3 Trip Survey

1. Participant ID?
2. Trip Date and Time?
3. Which word best describes your mood **before** your trip started?
    a) Happy
    b) Calm
    c) Stressed
    d) Fatigued
    e) Angry
4. Which word best describes your mood **during** your trip?
    a) Happy
    b) Calm
    c) Stressed
    d) Fatigued
    e) Angry
5. Please select which of the following events happened while you were driving.
    a) Sudden braking to avoid a pedestrian/cyclist/car
    b) Hostile behaviour from another driver
    c) Accident
    d) Heavy traffic
    e) None of the above (uneventful)

3.4 Driving Score

The telematic device records GPS and engine data for each driver. The engine data include acceleration forwards and braking (AccX), acceleration side to side (AccY), acceleration up and down (AccZ), GPS location, trip distance and number of times the driver "speeds" along with the distance and time spent speeding. Acceleration data are recorded at small increments in time, as shown in Table 2. For example, in the third row of Table 2, for the driver identified as "BB", at 2:34 pm in their first recorded trip, a braking event was recorded at -2.30 m/s^2.

Speeding, on the other hand, is a user-defined "rule" within the portal. A sample speeding report is shown in Table 3. For example, for the driver identified as "BB", during their 5th trip, at 2:50 pm, the driver was speeding for 0.6879 miles.

The driving score penalizes higher levels of acceleration, braking, cornering and speeding (T. S. Seecharan, 2021). To calculate the driving score, three levels were created for acceleration, braking and cornering to incorporate mid-range driving. Thresholds were chosen based on previous research on the effect of hard acceleration on vehicle fuel economy and passenger safety (Boodlal & Chiang, 2014). A speeding event for a driver depends on the posted speed limit of the road; therefore, a mid-range level for speeding was not designed. Instead, the trip length was recorded along with the length of time spent speeding.

Telematic devices collect continuous driving data and report them as discrete data at small time increments. In a trip – defined as from when the driver starts the car, drives, and then turns off the car –acceleration, braking, left cornering, right cornering and car speed are discrete values. Each discrete recording of acceleration, braking, left cornering, or right cornering is termed an "event". Each positive acceleration event is defined as $\boldsymbol{AccXPos_i}$, each negative acceleration event is $\boldsymbol{AccXNeg_i}$, each right turn event is $\boldsymbol{AccYNeg_i}$ and each left turn event is $\boldsymbol{AccYPos_i}$. In one trip, depending on the length, there are many of these events. The scoring system for

Table 2 Sample acceleration report

DriverID	TripID	time	description	value
BB	1	2:34:56 PM	AccX	0
BB	1	2:34:56 PM	AccY	0
BB	1	2:34:56 PM	AccY	−2.30
BB	1	2:35:02 PM	AccX	0
BB	1	2:35:02 PM	AccY	0
BB	1	2:35:39 PM	AccX	0
BB	1	2:35:39 PM	AccY	0
BB	1	2:35:39 PM	AccX	2.48
BB	1	2:35:42 PM	AccX	0
BB	1	2:36:05 PM	AccX	0
BB	1	2:36:05 PM	AccY	0
BB	1	2:36:06 PM	AccY	−2.83

Table 3 Speeding distance recorded for driver "BB"

DriverID	TripID	time	Distance (miles)
BB	5	14:50:53	0.688
BB	5	14:53:40	0.592
BB	5	14:54:30	1.28
BB	5	14:56:50	0.495

each metric is shown in Table 4. The thresholds were chosen from GPS tracking companies' websites (linxup, n.d.; Broughall, 2020).

The value of the event is checked against the threshold. For acceleration, braking, left cornering, and right cornering, each event is assigned a value of 0, 1, or 2 depending on its comparison to the thresholds. Using these values, the acceleration, braking, right cornering, and left cornering scores are calculated using Eqs. (1), (2), (3), and (4), respectively.

$$Accel = \left(\frac{\sum_{i=1}^{NAcc} AccXPos_i}{2 \times NAcc} \right) \times 10 \tag{1}$$

$$Brake = \left(\frac{\sum_{i=1}^{NBrk} AccXNeg_i}{2 \times NBrk} \right) \times 10 \tag{2}$$

$$Right = \left(\frac{\sum_{i=1}^{NRCrn} AccY_i}{2 \times NRCrn} \right) \times 10 \tag{3}$$

$$Left = \left(\frac{\sum_{i=1}^{NLCrn} AccY_i}{2 \times NLCrn} \right) \times 10 \tag{4}$$

In one trip, there will be a total number of acceleration events labelled ("NAcc"); a total number of braking events labelled ("NBrk"), a total number of right turn events labelled ("NRCrn") and a total number of left turn events labelled ("NLCrn"). As described above, each acceleration event, $AccXPos_i$,is assigned 0, 1 or 2 depending on the range in which the event falls. For example, an acceleration event of 2.83 m/s^2 is considered "Soft" and assigned a value of two. The assigned values for all these acceleration events are then summed ($\sum_{NAcc}^{i=1} AccXPos_i$). The best possible

Table 4 Scoring system for the driving score

Metric	Range	Score	Level
$AccXPos_i$	$AccX_i > 3.83ms^2$	0	Hard
	$2.83ms^2 < \mathrm{AccX}_i \leq 3.83ms^2$	1	Medium
	$0 < \mathrm{AccX}_i \leq 2.83ms^2$	2	Soft
$AccXNeg_i$	$AccX_i < -3.73ms^2$	0	Hard
	$-2.73ms^2 \leq AccX_i \leq -3.73ms^2$	1	Medium
	$-2.73ms^2 < AccX_i < 0$	2	Soft
$AccYNeg_i$	$AccY_i < -3.75ms^2$	0	Hard
	$-3.75ms^2 \leq AccY_i < -1.875ms^2$	1	Medium
	$-1.875ms^2 \leq AccY_i \leq 0$	2	Soft
$AccYPos_i$	$AccY_i > 3.75ms^2$	0	Hard
	$1.875ms^2 < \mathrm{AccY}_i \leq 3.75ms^2$	1	Medium
	$0 < \mathrm{AccY}_i \leq 1.875ms^2$	2	Soft

acceleration score will be the case in which all acceleration events are soft ($2 \times NAcc$). For a trip containing 10 acceleration events, the best possible score a driver can obtain would be 20 if all the acceleration events are soft. The same process is repeated for braking, right cornering, and left cornering.

In the case of speeding, the driver's road speed is compared with the road's posted speed limit using the GPS capability of the G09 device. Since data were recorded on roads within the United States, speed is communicated in terms of miles per hour. Within a trip, the telematic device records the number of times the driver was found speeding (*SpdFreq*) (if speed >8 mph over the posted speed limit) and the distance spent speeding. A speeding score is then the length of the trip not spent speeding divided by the total trip length, as shown in Eq. (5).

$$Speed = \frac{L_S^{'}}{L} \times 10 \tag{5}$$

where $L_S^{'}$ is the length of a trip not spent speeding and L is the length of a trip.

Finally, the driving score is the weighted average of the individual scores as shown in Eq. (6).

$$\begin{aligned} Driving\ Score = {} & 0.3(Speed) + 0.2(Accel) + 0.2(Brake) \\ & + 0.15(Right) + 0.15(Left) \end{aligned} \tag{6}$$

This type of weighted score was developed to: (1) be easy for the drivers to understand and (2) give more weight to metrics that are contributors to road traffic accidents. In addition to seeing a driving score, drivers see a breakdown of their scores on a radar plot. An example is shown in the example.

4 Results

Table 5 shows, for each driver, the trip driving score along with their self-reported mood pre- and posttrip. From Table 5, the data in the column titled "Mood 1" represents their pretrip moods, and the data in the column titled "Mood 2" represents their posttrip moods. The possible moods were "C" – calm; "F" – fatigued; "H" – happy; and "S" – stressed. For ten drivers, 48 trips of complete data were recorded.

4.1 EDA Data

Although a survey can gain some insight into the self-reported emotional states of drivers, it becomes tedious for drivers to complete a survey prior to each driving trip. Their EDA attempts were recorded to gain insight into their physiological

Table 5 The driving score, self-reported mood, and descriptive EDA data for each trip

Driver	TripID	Driving Score	Mood 1	Mood 2	EDA				
					Mean	Median	Std Dev	Max	Skew
CB	1	9.87	C	C	1.219	1.16	0.308	2.4	0.897
CB	2	9.44	H	C	2.723	2.75	0.525	4.626	−0.189
CB	3	10	F	C	0.247	0.231	0.0716	0.886	0.378
CB	4	9.81	S	C	1.36	1.34	0.481	3.477	0.118
DH	1	8.53	C	H	2.305	1.97	0.739	4.936	0.722
DH	2	8.73	H	H	0.279	0.264	0.0627	0.437	0.834
DH	3	9.2	H	C	0.333	0.293	0.108	0.64	1.04
DH	4	8.91	C	S	0.446	0.435	0.0769	0.733	0.447
DH	5	8.63	S	C	0.762	0.766	0.123	1.105	−0.0195
DK	1	9.05	F	F	0.324	0.276	0.192	1.165	1.22
DK	2	8.72	H	H	0.671	0.54	0.498	2.554	1.15
DK	3	8.62	H	H	2.336	2.4	0.805	4.366	−0.534
DK	4	9.4	C	S	2.141	2.29	0.753	4.251	−1.085
DK	5	9.13	C	C	0.0726	0.0794	0.0369	0.407	−0.232
GT	1	8.46	S	S	1.682	1.64	0.408	3.506	0.648
GT	2	8.71	H	H	1.101	0.988	0.441	2.43	0.388
GT	3	8.72	C	C	0.186	0.182	0.0857	0.565	0.767
GT	4	8.2	S	S	0.0692	0.0653	0.0291	0.154	0.496
GT	5	8.55	C	C	0.0365	0.0359	0.00681	0.0807	1.1
WW	1	8.55	C	C	0.54	0.555	0.174	1.34	0.391
WW	2	8.16	C	H	0.49	0.464	0.102	0.782	0.628
WW	3	9.02	C	C	0.204	0.15	0.0931	1.144	1.99
WW	4	8.6	C	C	0.298	0.289	0.0243	0.556	2.63

(continued)

Table 5 (continued)

Driver	TripID	Driving Score	Mood 1	Mood 2	EDA				
					Mean	Median	Std Dev	Max	Skew
WW	5	8.87	C	S	0.378	0.371	0.0558	0.84	2.27
JL	1	8.2	C	C	0.495	0.507	0.121	1.617	−2.2
JL	2	8.35	S	H	0.376	0.406	0.146	1.161	−0.975
JL	3	8.57	H	C	0.354	0.37	0.0865	1.006	−2.82
JL	4	8.5	H	H	0.211	0.25	0.0985	0.738	−1.1
JV	1	8.34	C	C	2.997	2.86	0.687	5.759	0.902
JV	2	9.11	C	C	1.071	0.836	0.79	3.376	0.55
JV	3	8.37	C	C	0.538	1.66	0.473	2.584	−0.24
JV	4	8.51	C	C	0.614	0.151	0.662	2.438	0.698
BB	1	8.11	F	S	0.11	0.11	0.0167	0.176	0.101
BB	2	8.67	H	C	0.577	0.533	0.187	1.172	0.389
BB	3	9.06	H	C	0.0887	0.0923	0.0153	0.119	−0.755
BB	4	8.76	S	S	0.072	0.0769	0.0158	0.104	−0.652
BB	5	9.23	F	C	0.221	0.127	0.183	1.925	1.58
WM	1	8.47	C	C	0.189	0.19	0.0119	0.229	−1.5
WM	2	8.43	C	F	0.277	0.285	0.107	0.602	0.039
WM	3	8.18	S	C	0.771	0.391	1.294	8.836	3.96
WM	4	8.62	F	F	0.173	0.177	0.0511	0.612	3.05
WM	5	8.63	C	C	0.185	0.188	0.0285	0.671	1.04
AOE	1	8.66	C	H	0.118	0.122	0.0263	0.2	−0.913
AOE	2	8.43	H	H	0.0867	0.091	0.0332	0.204	−0.397
AOE	3	8.47	F	C	0.0705	0.0769	0.0381	0.702	1.25
AOE	4	8.57	H	H	0.0537	0.0423	0.046	0.326	1.43
AOE	5	9.25	H	H	0.16	0.112	0.125	0.467	1.02

states while driving. From Fig. 2, the EDA varies by driver and by trip. The driver CB stated being calm for all four recorded trips. However, Fig. 2 shows considerable variability in the distribution of the driver's recorded EDA. The EDA distribution was lowest for Trip3 and highest for Trip2. Interestingly, CB's driving score was highest during Trip3 and lowest during Trip2. Sample boxplots for participants DH and DK are also shown in Fig. 2.

Overall, the average driving score was 8.75, median = 8.63, standard deviation = 0.445, and interquartile range = 0.565. When drivers reported being stressed prior to driving, the average score = 8.67; if the drivers were calm, the average driving score = 8.72. This shows some preliminary evidence that when drivers are "Stressed" prior to driving, their scores are lower than when they are "Calm". For drivers who reported feeling stressed while driving (Mood 2 = "S"), the average driving score = 8.67, and if they reported feeling calm while driving (Mood 2 = "C"), the average driving score = 8.85. Again, this suggests that drivers who reported feeling calm exhibited more eco-driving habits.

Figure 3 shows the distribution of driving scores by Mood 2. For drivers in the "C" state, the data are skewed towards higher driving scores meaning that most of the driving scores are toward the left of the mean. When drivers self-reported being stressed, "S", the upper quantile is smaller than the lower quantile, and the data are skewed to the left, with lower driving scores pulling the mean to less than the median. This suggests that a driving score of 10 is more likely when the drivers are calm. Additionally, the median of the driving scores in the "C" state is lower than when drivers reported being stressed.

Figure 4 shows a plot of the driving score and the average EDA, and Table 6 shows the correlations of the driving score with the EDA descriptive metrics. Interestingly, all correlations are positive, but they are all small. The correlations between the driving score and sdEDA, the driving score and MaxEDA, and the driving score and Skew are all close to zero, indicating no relationship. The correlation between the driving score and mean EDA is greater but still very small. Therefore, given the data, there is no statistically significant evidence to show that when the EDA descriptive statistics increase, the driving score increases.

4.2 Observations by Driver

All drivers are unique, and thus, their EDA activities vary. It is difficult to assign an EDA value or range that identifies a "stressed" state for all drivers. For this reason, driving performance is observed for each driver. Table 7 provides a brief description of the observations by driver. The analysis of driver experiences and behaviours during specific trips, considering driving scores, EDA, and reported moods, reveals intriguing patterns. Notably, drivers who achieved their best driving scores often exhibited EDA characteristics aligned with their reported emotional states. For instance, drivers with calm moods tended to record lower average EDA, while those with stress reported higher EDA. Interestingly, the direction of

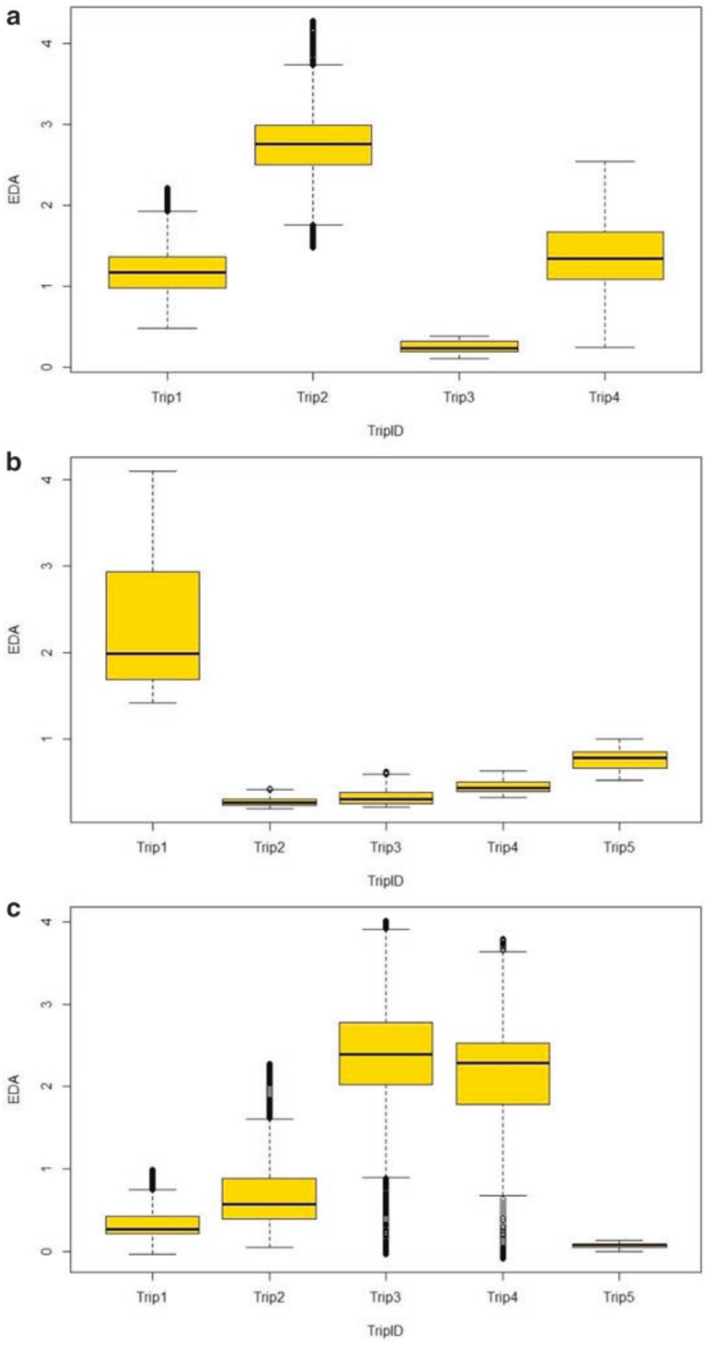

Fig. 2 Boxplots of the EDA distribution for three drivers: (**a**) CB, (**b**) DH, and (**c**) DK

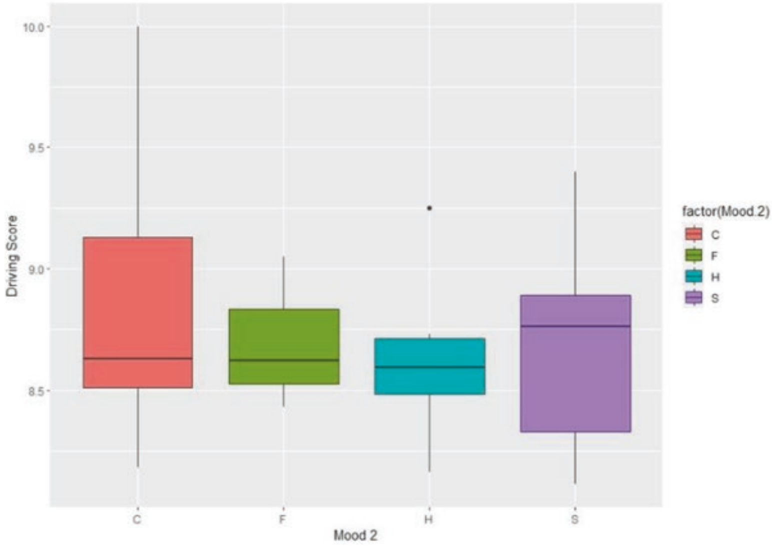

Fig. 3 Distribution of driving scores by mood 2

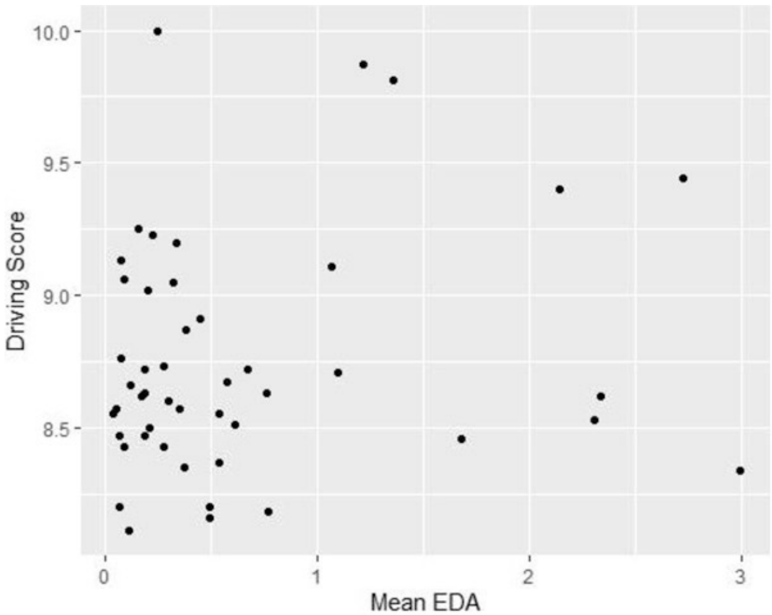

Fig. 4 Driving Score and mean EDA for all trips

Table 6 Correlation matrix

	Mean EDA	Sd EDA	Med EDA	Max EDA	Skew EDA
Driving score	0.1607	0.0318	0.1493	0.0377	0.0366

Table 7 Intra-driver observations

Driver	Comments
CB	This driver recorded the best driving score during trip 3. The driver said they felt calm during this trip. This seems to be reflected in their EDA since the mean was the lowest.
DH	The best driving score was recorded for trip 3. The mean EDA was second lowest with the greatest positive skew meaning most EDA was to the left of the mean.
DK	The best driving score was recorded for trip 4. The driver reported feeling stressed, and their mean EDA was the second highest. Skewness was most negative for trip 4, meaning most EDA was to the right of the mean.
GT	The best driving score was recorded for trip 3. The mean EDA was in the middle.
WW	The best driving score was recorded for trip 3. This was also the drivers lowest average EDA with a positive skew. This driver drove best when their EDA distribution was lowest.
JL	The best driving score was recorded for trip 3. The mean EDA was the second lowest, but the skew was the most negative meaning the distribution of EDA was to the right of the mean.
JV	The best driving score was recorded for trip 2. Their mean EDA was the second highest.
BB	The best driving score was recorded for trip 5. Their mean EDA was the second highest during this trip.
WM	The best driving score was recorded for trip 5. Their mean EDA was the second lowest.
AOE	The best driving score was recorded for trip 5. Their mean EDA was the second highest.

skewness in EDA distributions also seemed to correspond to driving performance, with positive skew linked to better performance for some. These findings underscore the potential interplay between physiological responses, emotional states, and driving outcomes, suggesting avenues for deeper investigations into the complex relationships among human emotions, physiological signals, and driving performance.

4.3 Cluster Analysis

Hierarchical clustering with the "ward.D2" linkage method is used to search for patterns within clusters. Ward's method minimizes the total within-cluster variance. Ward D2 considers the distance between the centroids of the clusters being merged as opposed to the Ward D methods that consider the distance between the individual data points and the mean of the merged cluster. Empirically, Ward D2 tends to produce more compact and spherical clusters, while Ward D may be more sensitive to outliers. Figure 5 shows the generated dendrogram.

From Fig. 6, the Mean EDA and Median EDA show separable clusters. There is a difference in the mean EDA and median EDA between clusters. Cluster 2 has the highest mean and median EDA distribution. The median of the driving scores in Cluster 2 is very close to Cluster 3. However, because of the shape of the boxplot, many of the driving scores fall to the right of the median. Cluster 1 seems to have the "best" distribution of driving scores, in which the scores are generally higher

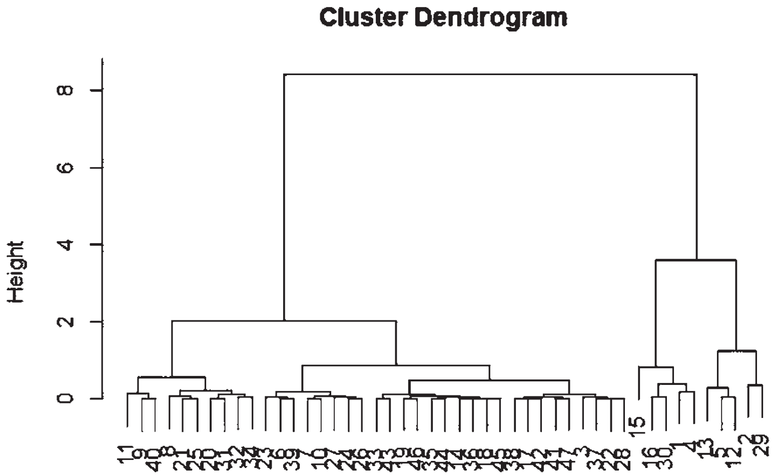

Fig. 5 Dendrogram from cluster analysis

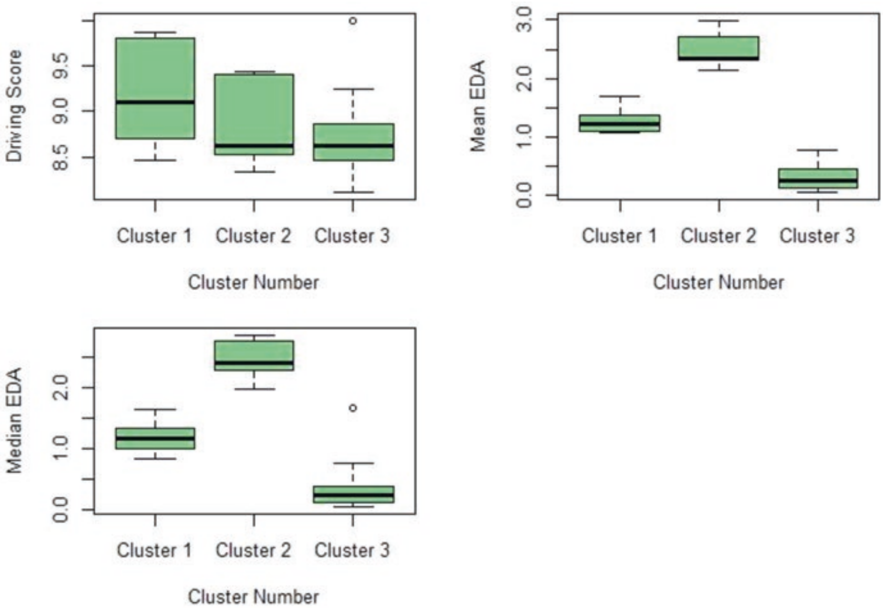

Fig. 6 For each cluster, the above boxplots compare the driving score, mean EDA, and median EDA

than those of the other two clusters. Interestingly, the EDA values are not the lowest and not the highest. This indicates some evidence that driving scores are best when the drivers' EDA is not low but not too high.

5 Discussion

This paper presented a pilot study to investigate the relationship between EDA and eco-driving performance. For fleet managers, stress-related issues can results in increased costs for companies due to accidents, increased downtime, and higher rates of absenteeism. By addressing drivers' stress levels, fleet managers can mitigate these financial burdens. Driver stress can negatively impact the physical and mental health of employees. Chronic stress can lead to various health issues, including hypertension, anxiety, and depression. Caring for drivers' well-being fosters a healthier and more motivated workforce. Stressed drivers are more likely to violate traffic laws and regulations, potentially leading to legal consequences and penalties for the company. A supportive work environment that prioritizes drivers' well-being can improve employee satisfaction and retention rates. Happy and supported drivers are more likely to stay with the company long-term. Fleet companies are responsible for their drivers' actions on the road. High stress levels may lead to aggressive driving behaviours or customer service issues, which can damage the company's reputation and lead to a loss of clients.

Ten drivers wore an Empatica E4 wristband while they completed 5 trips of at least 5 miles in length. The Geotab G09 telematics device was used to record engine data, including acceleration forward, braking and acceleration side to side. It also has GPS capability to identify when speeding occurs. An eco-driving score was used to measure their level of eco-driving. Lower scores indicate fewer eco-driving behaviours.

The highest observed correlation was between the driving score and mean EDA, but this correlation was not statistically significant. Although positive – higher driving scores indicated higher mean EDA – this correlation was not statistically significant. A cluster analysis was also performed to look for patterns within clusters. The cluster dendrogram shows that three separable clusters can be achieved. From Fig. 6, the driving scores in cluster 1 had the highest mean and distribution towards higher scores than the other two clusters. Interestingly, this cluster contained neither the highest nor lowest mean and median EDA. This indicates that the best driving performance for the 48 recorded trips occurred when the drivers were more emotionally aroused. This finding supports the Yerkes-Dodson Law that performance increases with physiological or mental arousal, but only up to a point. When levels of arousal become too high, performance decreases.

5.1 Study Limitations, Strengths, and Future Work

The strength of this study is that it uses naturalistic driving and wearable sensors to observe the eco-driving behaviours of drivers. The E4 sensor and G09 device are both minimally invasive. The preliminary results indicate the need for fleet managers to pay attention to the mental health and stress levels of their drivers. In-vehicle systems to monitor drivers' physiological states while driving.

One of the study limitations is the use of raw EDA data. Another way of analysing skin conductance is to separate it into its phase and tonic components. The phasic component, also known as the skin conductance response (SCR), is a relatively fast variation in skin conductance, while the tonic component, also known as the skin conductance level, reflects slow variation (Benedek & Kaernbach, 2010; Imtiaz et al., 2020). In this study, the phasic component is more significant, as the participant could experience abrupt situations, e.g., sudden braking and sudden accidents. A future study will decompose the EDA signal into its phasic and tonic components and analyse eco-driving performance as the drivers' phasic component changes. A "true baseline", which is the driver's EDA during a calm emotional state, was not recorded in this study. For a future study that uses phasic data, a true baseline is required. In addition to the small sample size, this study limits the sample to young drivers. Future studies can investigate whether similar patterns are observed in different age groups and for a larger sample size.

Vehicle emissions are a major contributor to greenhouse gas (GHG) emissions worldwide. In 2021, the transportation sector was the largest source of GHG emissions in the United States (U.S.) (United States Environmental Protection Agency, 2022). A future study can investigate the relationship between driver's emotional state and their decisions toward sustainable transportation.

Understanding driver stress empowers asset managers to create safer, more efficient, and driver-centric operations. By integrating stress awareness into asset management practices, the transportation industry can achieve higher levels of performance, safety, and driver satisfaction.

6 Conclusion

In this work, the relationship between driver emotional arousal and eco-driving behaviours using naturalistic driving behaviour was investigated. Drivers wore a wristband sensor to record their EDA while driving. An eco-driving score was built using engine data recorded using a telematic device plugged into the OBD II port of drivers' personal vehicle. This pilot study recorded 48 trips of five miles in length from 10 drivers. The results follow the Yerkes-Dodson law. The drivers' best driving scores were observed when they were emotionally aroused but not as the highest level. These results point to the possibility that attention must be given to the emotional state of drivers before they drive. Future work will increase the sample size, incorporate different routes, increase the age range.

Ethics Approval This study received approval from the Institutional Review Board (IRB) with study code STUDY00015895.

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