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Article

Personal Informatics and Negative Emotions during Commuter Driving: Effects of Data Visualization on Cardiovascular Reactivity & Mood

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Abstract

Mobile technology and wearable sensors can provide objective measures of psychological stress in everyday life. Data from sensors can be visualized and viewed by the user to increase self-awareness and promote adaptive coping strategies. A capacity to effectively self-regulate negative emotion can mitigate the biological process of inflammation, which has implications for long-term health. Two studies were undertaken utilizing a mobile lifelogging platform to collect cardiovascular data over a week of real-life commuter driving. The first was designed to establish a link between cardiovascular markers of inflammation and the experience of anger during commuter driving in the real world. Results indicated that an ensemble classification model provided an accuracy rate of 73.12% for the binary classification of episodes of high vs. low anger based upon a combination of features derived from driving (e.g. vehicle speed) and cardiovascular psychophysiology (heart rate, heart rate variability, pulse transit time). During the second study, participants interacted with an interactive, geolocated visualisation of vehicle parameters, photographs and cardiovascular psychophysiology collected over two days of commuter driving (pre-test). Data were subsequently collected over two days of driving following their interaction with the dynamic, data visualization (post-test). A comparison of pre- and post-test data revealed that heart rate significantly reduced during episodes of journey impedance after interaction with the data visualization. There was also evidence that heart rate variability increased during the post-test phase, suggesting greater vagal activation and adaptive coping. Subjective mood data were collected before and after each journey, but no statistically significant differences were observed between pre- and post-test periods. The implications of both studies for ambulatory monitoring, user interaction and the capacity of personal informatics to enhance long-term health are discussed.

Keywords: Affective Computing, Biomedical Informatics, Cardiology, Data Visualization, Pervasive Computing, Vehicle Driving, Wearable Computers

1 Introduction

Negative emotions, such as anxiety, anger and depression, are associated with inflammatory processes in the human body (Camacho, 2013; Steptoe, 2007). This process of inflammation is directly linked to those biological processes that underpin the development of cardiovascular disease, such as atherosclerosis (Hansson, 2005; Suls & Bunde, 2005). The relationship between disease and negative emotions, such as anxiety (Thurston, 2013) and anger (Suls, 2013), is moderated by the cumulative influence of inflammation over the life course of the individual (Juster, 2010). According to the model of preservative cognition (Brosschot et al, 2010), this association is pernicious because physiological changes underpinning inflammation, which coincide with the experience of negative emotional states, can be sustained and often occur outside the conscious awareness of the individual (Lovallo, 2005). Previous research has associated a link between changes in heart rate variability (HRV) and biological markers of inflammation and reduced emotional regulation (Henriques et al., 2011). Both Low Frequency (LF) and High Frequency (HF) measures of HRV are associated with blood-borne indicators of inflammation, such as proinflammatory cytokines (e.g. Interleukin-6) and C-Reactive Protein (CRP) (Cooper et al, 2015), i.e. reduced HF activity of HRV is associated with increased activation of the parasympathetic nervous system and reduced inflammation.

Driving represents a common activity undertaken by millions of people each day that is associated with negative emotions and inflammation. The average American driver spends 46 minutes driving per journey, with UK drivers averaging 22 minutes per car trip (Dunn, 2015; National Travel Survey 2014, 2015). Over a period of weeks and months, the cumulation of these journeys amounts to a significant proportion of time spent by individuals on the road. The average driver can expect to experience negative emotions, such as anger (e.g. actions of other drivers) and anxiety (e.g. journey schedules), on a daily basis. These negative emotions can have a cumulative and detrimental influence on long-term cardiovascular health. For example, there is a positive association between traffic congestion and elevated blood pressure due to journey impedance (Schaeffer et al, 1988; Stokols et al, 1978). The development of driving sensors (Welch, 2019) and lifelogging technology with wearable physiological sensors represents one way to raise awareness of unconscious physiological changes associated with emotion during real-world driving.

1.1 Wearable Sensors and Lifelogging Technology

The development of wearable technology that utilises physiological sensors and is capable of delivering feedback on the process of inflammation in everyday life could be valuable for long-term health, because: (1) it would create explicit awareness of the physiological change associated with an episode of anger or anxiety, and (2) increased awareness of these physiological changes in everyday life could act as a driver for the development of coping strategies that are adaptive and ameliorate the influence of negative emotions/inflammation on long-term health (Ganzel, 2010). The Levels of Emotional Awareness (LEA) theory (Lane & Schwartz, 1987) made a distinction between implicit/preconscious awareness of an emotion (e.g. bodily sensation) and explicit awareness where one is not only aware of a particular emotion but capable of verbally expressing the emotion in question. Recent work demonstrated that explicit awareness of negative emotion was a necessary precondition for the development of adaptive coping strategies, such as reappraisal (Subic-Wrana et al, 2014).

It is proposed that mobile lifelogging technology, where data are gathered from multiple sensors during everyday life, can promote the requisite self-reflection to promote coping strategies and behaviour change. The effectiveness of lifelogging technology to support the development of adaptive coping strategies depends on the provision of feedback to the individual and the way in which the user interacts with their own data.

The process of measurement and inference is central to the development of a mobile lifelogging platform and provision of feedback during everyday life. Both miniaturization of sensors and increased computational power enables mobile devices to capture a variety of personal data, including physiological signals and environmental information. The availability of this hardware affords an opportunity to collect data "in the wild" within real-life situations and present these data to individual users. For example, Hänsel et al (2016) utilised a smartwatch to log current emotional states, via self-reports, and collect sensing data, including location, heart rate, physical activity, ambient noise and wrist movements. A smartphone application was also developed to enable participants to review their own data. Singh et al. (2014) collected photoplethysmogram (PPG), galvanic skin response (GSR) and respiration data to detect driver stress. Using a cascade forward neural network (CASFNN), their system achieved an overall accuracy of 80% when drivers drove around three pre-planned driving setups. In other works, the *GStress* model (Vhaduri et al, 2014) used smartphone GPS traces to estimates driver's stress using a generalized linear mixed model (GLMM) and captured a positive correlation coefficient (0.72) between subjective stress and GPS. Muaremi et al (2013) utilised a smartphone to collect audio, physical activity, location and communication data during the day and a chest belt to collect heart rate variability data during sleep. Results of their multinomial logistic regression model indicated a maximum accuracy of 61% for a multiclass (low, moderate, and high stress) model. Whilst Castaldo et al (2016) attempted to detect changes in mental stress by collecting HRV features via a 3-lead electrocardiogram (ECG) from students during an oral exam (stress period) and under controlled resting conditions (calm period); they reported that the C4.5 tree algorithm obtained a maximum accuracy of 79% classification between exam and rest.

In other lifelogging works, *Affective Diary* (Lindstrom et al, 2006) is an affective diary system that records pulse, step count and acceleration, as well as mobile phone data, including texts, multimedia messages, photographs and Bluetooth. The data that is collected is subsequently transformed into ambiguous, abstract colourful shapes. The purpose of this system was to allow users to organise, reflect and alter their diaries. Similarly, *AffectAura* (McDuff et al, 2012) is a system that continuously tracks valence, arousal and engagement and then transforms these data into the *AffectAura* lifelog visualisation, enabling users to reflect on their emotional experiences over extended periods of time. The system captured facial expressions, posture, speech, electro-dermal activity (EDA) via a wearable wrist sensor, location via GPS, file activity of web URLs visited, documents opened, applications used and emails sent and received and calendar information. The interface was structured in a timeline, with affective states visualised as coloured bubbles. Results indicated that participants found the interface useful and could "reason forward and backward in time about their emotional experiences" (McDuff et al., 2012). Meanwhile, *FEEL* (Ayzenberg et al, 2012) is a lifelogging system that measures EDA, via a wrist-worn commercial sensor, and captures mobile phone data to determine the context of social interactions. The data is analysed in real-time to associate stress (via EDA) with events captured via the mobile phone (e.g. emails, phone calls, etc.). The data is then combined into a digital journal of calendar/list events where the user can "reflect on his/her physiological responses" (Ayzenberg et al, 2012). A limited evaluation of the system was undertaken by one user over 200 hours, whereby it was reported that the system enabled him to better recall past stressful events.

While the availability of wearable sensors improves the ease of data collection, this type of ambulatory measurement is associated with significant challenges with respect to the collection of high-quality data (Rahman et al, 2014) and the mitigation of confounding factors (Fahrenberg et al, 2007). Extensive signal processing and data analysis is often necessary to remove confounds from these data in order to draw robust inferences about behaviour and emotional states in the real-world.

1.2 Personal Informatics and Data Visualisation

If a lifelogging system can collect physiological data in a way that is both sensitive and reliable for the detection of negative emotions in everyday life, the next challenge for the designer is to deliver effective feedback to the user about these data. Feedback from a mobile lifelogging platform can support a process of introspection by transforming implicit emotional experience into explicit self-awareness, and in doing so, creating a foundational level of knowledge for the development of reappraisal, acceptance and other adaptive forms of coping (Boden & Thompson, 2015).

Ubiquitous technologies, which are dedicated to personal informatics (Li et al, 2011) and the quantified self (Shin & Biocca, 2017) deliver feedback that is based upon objective data in order to enhance self-improvement (Gemmell et al, 2006) or support cognitive function (Dobbins et al, 2014) . It has been argued that personal informatics support behavioural change by allowing the user to *reflect* upon behaviour, *integrate* personal data with a sense of self and finally take *action* (Li et al, 2010). The ability of personal informatic technology to support this type of behaviour change is influenced by the *fidelity* of the user interface (e.g. how personal history is represented) and utility of feedback to *forecast* future actions and feelings (Hollis et al, 2017). However, naïve users often encounter a number of obstacles during interaction with their personal data. The sheer volume of the database combined with abstract visualisations (e.g. bar or line charts) can make it difficult to efficiently extract meaning, rendering the process of self-tracking burdensome and unrewarding (Rapp & Cena, 2016). In addition, the absence of context often prevents the identification of triggers in the environment that can promote desirable or undesirable behaviours (Choe et al, 2014). The presentation of data visualisation at the interface is an important design issue as real-time feedback of negative emotions can amplify those emotions and be counterproductive. The act of emotional regulation in situ can be cognitively demanding (Gross, 2002) hence feedback may be more constructive when delivered retrospectively at a time of the user’s choosing when they have sufficient cognitive capacity to reflect upon their data.

Previous research on visualisation of emotions includes *StressTree* (Yu et al, 2017), which is a heart rate variability (HRV) biofeedback system that transforms HRV data into a representation of a tree that metaphorically represents the health of the user as the growth pattern is affected by the users’ stress state. For example, when the user experiences high stress for a long period of time, the appearance of the tree grows more fragile. However, during periods of healthy balance the appearance of the tree is healthier. HRV was measured via a PPG sensor attached to the index finger. Participants reported that the visualisation promoted self-reflection of their behaviours but the interface perhaps would have been more suitable for visualisation on a mobile device, like a smartphone. Similarly, *Chill-Out* (Parnandi et al, 2014) is an adaptive biofeedback game that assists the user in developing relaxation skills by monitoring breathing. HRV and respiration were measured using a Bioharness sensor, whilst electrodermal activity (EDA) was measured using FlexComp Infinity encoder. Results indicated that playing *Chill-Out* led to lower arousal, in contrast to a non-biofeedback game and traditional relaxation methods, when participants were exposed to a stressor task. *Affective Health* (Sanches et al, 2010) is another stress management biofeedback mobile system that utilises a triaxial accelerometer, skin conductance, and three-lead ECG sensors to capture physiological data. The system was designed to allow users to see their own bodily reactions in real time and help them to identify stressful patterns in their data. The interface for this system consisted of two designs: layers and spirals, with colour representing arousal. They argued that feedback to the users should be presented using an interface design that encompassed properties, such as: ambiguity, openness to interpretation, interactive history, fluency and aliveness. *Cardiomorphologies* (Muller et al, 2006) included measures of breathing (via a respiratory strain gauge) and heart rate (via electrocardiogram (ECG), which were transformed into an interactive abstract visualisation of coloured rings. Results indicated "that the relationship between the visuals and the participants' mental and physical states leads them to a feeling of engagement" (Muller et al., 2006). A different approach was adopted by *StressEraser* (Moore, 2007), which is a hardware device that measured heart rate via pulse oximetry and visualised the heart rate signal as a simple wave, accompanied by an audible tone, which supported the user to develop deep breathing exercises to alleviate stress. Whilst *MoodWings* (MacLean et al, 2013) is a real-time biofeedback system that captures EDA and ECG data to detect stress during simulated driving. The system utilises a wearable butterfly that depicts the user's stress state through movement of the wings, which acts as an early warning system and physical interface. Results indicated that *MoodWings* resulted in safer driving but also significantly increased both self-perceived and biophysical stress.

The primary contribution of the current work was to create an interactive data visualisation in the lifelogging mode that provided users with feedback on "hidden" cardiovascular measures of inflammation during everyday life. The primary purpose of the data visualisation was to increase awareness of implications for long-term health that are associated with the experience of negative emotions during commuter driving. The secondary goal of the data visualisation was to function as an agent for behavioural change. Unlike most work in this area that uses real-time feedback, this visualisation of personal data delivers feedback retrospectively when participants are able to reflect on negative emotions and their precedents. Therefore, the novelty of the current work is twofold: (1) to allow participants to make an association between inflammation, health and emotional responses during commuter driving in order to gain insight into their emotional experiences, and (2) to evaluate whether this kind of interaction with personal data led to demonstrable change in subjective mood or cardiovascular physiology during subsequent episodes of commuter driving.

The work included in this paper had four main objectives. The first was to investigate whether there is an association between cardiovascular markers and the experience of negative emotion during commuter driving in the real-world. Secondly, we wished to establish whether variables captured during commuter driving, i.e. both cardiovascular physiology and vehicle parameters (e.g. speed of car), could successfully classify episodes of high and low anger. Both objectives were addressed through study one that consists of a data collection exercise of thirteen participants conducted over five consecutive days of commuter driving. The third goal of the paper was to develop an interactive data visualisation that integrated cardiovascular reactivity, driving parameters via geolocation in combination with still images. The purpose of this interactive visualisation was to provide users with sufficient insight to develop adaptive coping strategies with respect to negative emotion and cardiovascular reactivity during their daily commute. The specific parameters and measures that we adopted for the data visualisation were directed by the results of the first study, specifically the process of feature selection used for classification of low vs. high subjective anger. Given that the purpose of the interactive data visualisation was to promote adaptive coping strategies, the fourth objective was to evaluate the effects of data visualisation on subjective mood and cardiovascular psychophysiology. The second study in the paper describes a study where data were collected during two days of commuter driving (as in study one) as a pre-test period, then participants spent a period of time interacting with the data visualisation, before data were collected from two more days of commuter driving (post-test period). It was hypothesised that exposure to the data visualisation would enhance self-awareness and promote adaptive coping strategies, hence negative mood and cardiovascular reactivity will be reduced during the post-test phase.

2 Study One

2.1 Design of Study

Study one consisted of a data collection exercise to collect raw data over a period of five working days using the developed lifelogging platform (described below). This was a longitudinal data collection exercise designed to be integrated with participants' normal working routines. Prior to providing written consent, participants were presented with an Information Sheet giving full details of the study. Participants were instructed that physiology and other parameters would be monitored over a five-day period of commuter driving with two journeys per day (morning and evening). Participants were also required to complete a subjective mood questionnaire, STAXI-2 (see section 2.5) before and after each journey.

For logistic reasons, each participant was provided with full instructions on how to place and remove the disposable electrodes and how to check signal quality. This information was conveyed during a one-to-one training session with the experimenter in order to ensure that the set-up of apparatus was consistent and correct. Participants were told how to check that sensors had been activated and were logging data. The participants were also instructed on how to access the subjective mood questionnaire, via the smartphone.

Participants were required to drive for a minimum of 10 continuous minutes, over the same route to/from work. The time of the journeys varied from 10:44 minutes to 01:17:45 hours (mean = 32:12 minutes, SD = 12:27 minutes). Study one resulted in the collection of ~64 hours (408,113,095instances) of raw data over the data collection period.

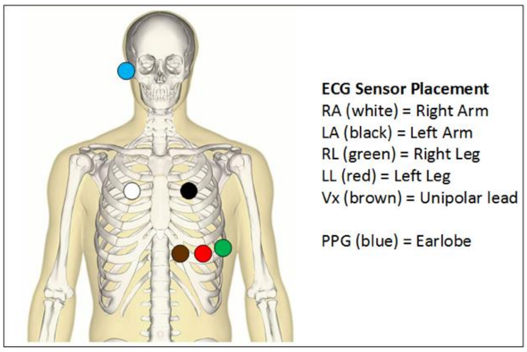
2.2 Participants

The participant sample included fourteen individuals – seven females and seven males, with an age range from 25 to 57 years (mean = 42.64, SD = 11.84). None of the sample had any history of heart disease or were taking medication that would influence cardiovascular activity. All protocols for recruitment and data collection were approved by the institutional Research Ethics Committee prior to commencement of data collection. However, two participants data were excluded, as one did not complete the entire study and another participants data was unusable.

2.3 Lifelogging Platform

The lifelogging platform consisted of a smartphone (Samsung™ Galaxy S5/S6), a Shimmer3™ accelerometer and two wearable Shimmer3™ sensor units (see Figure. 1a). The latter were used to capture raw electrocardiography (ECG) and photoplethysmogram (PPG) signals. ECG was obtained via a 5-lead ECG unit attached to the torso of the individual, whilst PPG was obtained via an optical pulse ear-clip (see Figure. 1b). The Shimmer3™ sensors were configured at a sample rate of 512 Hz and data was stored on the internal microSD card. Vehicle speed was calculated from the raw Shimmer3™ acceleration data, which was captured in metres per second squared (m/s^2). A full and detailed description of this data collection platform has been published elsewhere (Dobbins and Fairclough, 2018).

a)



b)

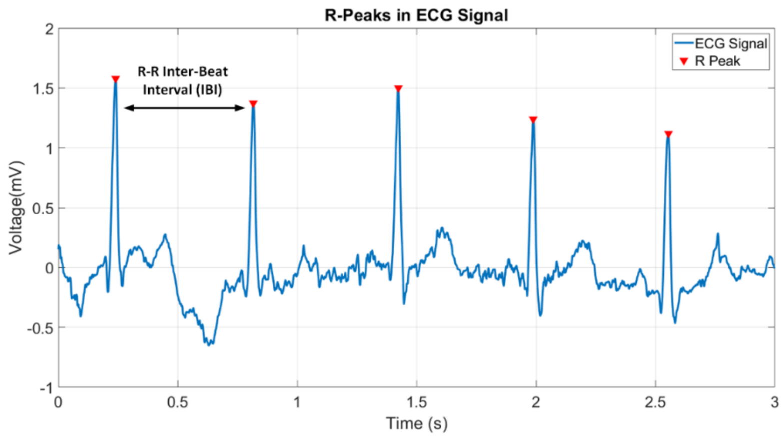
Figure. 1. a) Lifelogging hardware platform that consisted of two Shimmer3™ wearable sensor units (1) electrocardiography (ECG) and (2) photoplethysmogram (PPG), (3) a smartphone and (4) Shimmer3™ accelerometer. b) Sensor placement of the ECG leads on the torso and PPG optical pulse ear-clip to the ear lobe

2.4 Signal Processing of Physiological Data

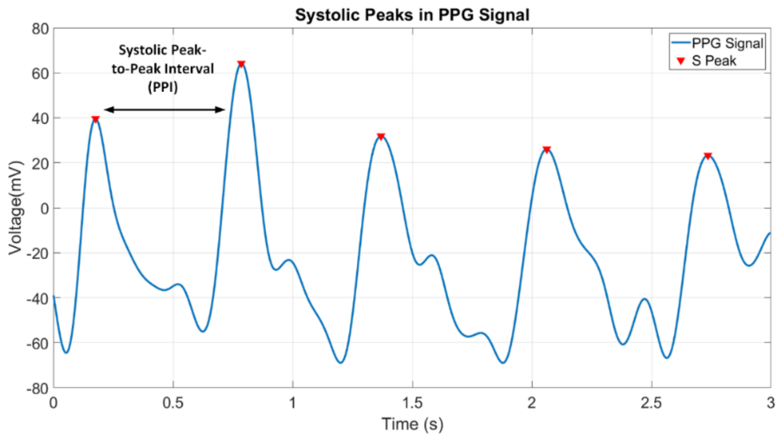
For the purposes of the current paper, signal processing procedures are described briefly, a full and detailed description is available (Dobbins and Fairclough, 2018). Collection of psychophysiological data in the field is particularly susceptible to noise. Therefore, it was important to pre-process data from the wearable Shimmer3™ sensors before cardiovascular measures were extracted; these data were analyzed using MATLAB vR2016a.

Raw ECG signals record the electrical activity of the heart. The beats of the heart are identified from waves known as the QRS complex. The length of time between consecutive R waves (or beats/peaks) is known as the Inter-Beat Interval (IBI) (see Figure 2a). Once a heartbeat occurs, blood flows to different areas of the body and reaches a peak before it progressively decreased. A raw PPG signal records the rate of blood flow, which occurs after a heartbeat, as two types of peaks – systolic and diastolic. We were interested in the systolic Peak-to-Peak Interval (PPI) as these are the maximum peaks within the PPG signal (see Figure 2b). Artefacts in both signals were identified and corrected, including missing peaks and false positives.

A number of electrocardiography features were extracted from the raw psychophysiological data. These features included: heart rate (beats per minute, bpm) and heart rate variability (HRV), which were measured in the time and frequency domain. HRV measures included the Root Mean Square of the Successive Difference of RR intervals (RMSSD), which is a temporal measure of parasympathetic heart rate activity, with low values being indicative of reduced parasympathetic activation (Berntson et al., 1997). Features from the frequency domain to index heart rate variability, were also extracted, including: Low Frequency (LF), power in spectrum between 0.04 – 0.15 Hz, and High Frequency (HF), power in spectrum between 0.15 – 0.4 Hz, measures of HRV (Electrophysiology, 1996).



a)



b)

Figure 2. Example of detected a) R peaks (Inter-Beat Interval) in the ECG signal and b) Systolic Peak-to-Peak Interval (PPI) in the PPG signal

A heart-beat can be measured using an ECG or the photoplethysmogram (PPG) sensors, which records perfusion of blood to the subcutaneous tissue of the skin. When the heart beats, blood is pumped to peripheral vasculature and a pressure pulse can be detected via PPG. The time needed by this pulse wave to exit the heart and reach the peripheral vasculature is expressed as the Pulse Transit Time (PTT) (Obrist et al., 1979). Hence, PTT is defined as the time delay between the R-peak of the ECG and the arrival of the corresponding pulse wave at a peripheral site, which was the ear lobe in the current study. PTT has been used to estimate blood pressure (Peter et al., 2014); it has a negative correlation with systolic blood pressure (He et al., 2013) (i.e. reduced PTT = increased blood pressure) and has been found to decrease in the presence of a social stressor (Hey et al., 2009). Hence, PTT was used as a proxy measure for blood pressure during the current study. The ECG/PPG data were segmented using 30-second non-overlapping windows to provide a common time basis for analysis.

2.5 Experimental Measures

Time and frequency domain features from the physiological data were extracted per 30 sec windows. These features included Inter-Beat-Intervals (IBI), heart rate (HR), root mean square of differences of successive RR intervals (RMSSD), low frequency power between 0.04 and 0.15 Hz (LF_HRV), high frequency power between 0.15 and 0.4 Hz (HF_HRV) and pulse transit time (PTT). Descriptive statistics related to speed were also extracted from the acceleration data, as well as time spent travelling in various speed bands, starting from 0 – 10 mph and calculated in increments of 10 mph blocks.

Subjective self-reported mood was also assessed via a shortened version of the State–Trait Anger Expression Inventory 2 (STAXI 2) subjective questionnaire (Spielberger, 1999). This questionnaire contained fifteen statements that participants scored their current feeling against on a Likert scale (1 = *not at all*, 2 = *somewhat*, 3 = *moderately so* and 4 = *very much so*). Responses were measured in terms of state anger (S-Ang), feeling angry (S-Ang/ F), feeling like expressing anger verbally (S-Ang/V) and feeling like expressing anger physically (S-Ang/P). The questionnaire were administered using a custom-built Android application that was running on the administered Samsung™ Galaxy S5/S6 smartphone.

2.6 Study One Results

One purpose of the first study was to assess the variables that were predictive of subjective anger experienced during each commuter journey. It was decided to focus only on those instances of journey impedance for the purpose of this classification, i.e. when drivers are stuck in stationary or very slow-moving traffic, as a negative driving scenario. All variables were averaged for each 30s epoch and journey impedance was defined by those epochs when the vehicle was travelling at an average speed of =< 11 mph.

The data were labelled using change scores related to feelings of negative emotions, which were derived from the category of feeling angry (S-Ang/ F) from the STAXI 2 subjective questionnaire. Change scores were calculated by subtracting the pre-drive responses away from the post-drive responses for each category. Drives that scored positively were deemed to indicate high feelings of anger had occurred, whilst negatively scoring drives indicated low levels of anger. Those that did not exhibit a change were scored as zero and were discounted.

Figure 3 illustrates the proportion of scores for each category. As it can be seen, the dataset is quite unbalanced, which is an issue for machine learning algorithms, as bias will form towards the majority class. To correct this issue, the minority class (i.e. high anger class) was oversampled using the Synthetic Minority Over-Sampling Technique (SMOTE), which is a common and accepted method for solving issues around unbalanced datasets (Chawla et al., 2002).

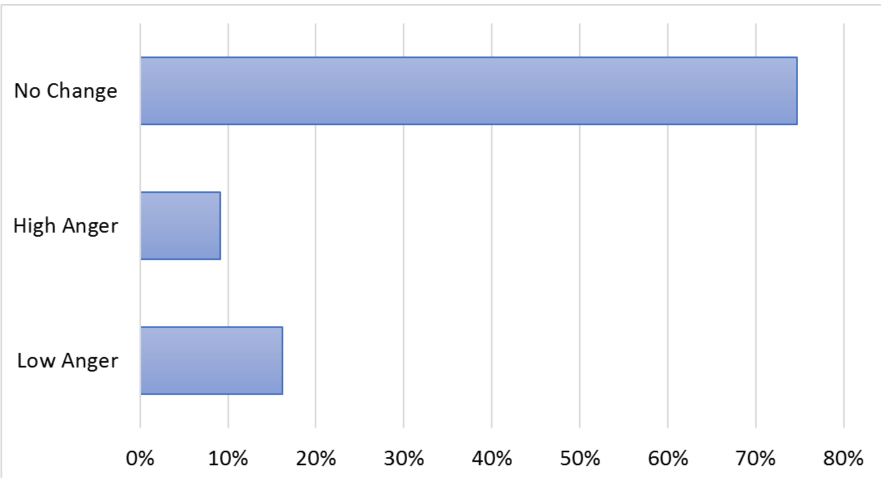


Figure 3. Proportion of STAXI 2 change scores that were used as the basis for labelling the data

Using the approach of previous work (Dobbins and Fairclough, 2018), the analysis consisted of independently evaluating the driving and physiology features separately and then collectively using an ensemble classifier that utilized Linear Discriminant Analysis (LDA), Decision Tree (DT) and k-Nearest Neighbours (kNN) classifiers. Features were selected independently from each dataset using the RELIEFF algorithm (Kononenko et al., 1997). This method uses a *k* nearest neighbour approach that averaged the contribution of all *k* nearest hits and misses and weighted this with the prior probability of each class to estimate the quality of the features. Using the RELIEFF algorithm, the following features were selected, per dataset:

- *Driving Features* dataset – Median Speed, Minimum Speed and 0-10 mph (time spent in this speed band)
- *Physiological Features* dataset – Mean HR, Mean HF_HRV, Mean PTT and STD PTT
- *Driving/Physiological Features* dataset – AM_PM (morning or evening drive), 0-10 mph (time spent in this speed band), Mean HR, Mean HF_HRV, Mean PTT and STD PTT

The results have been validated using repeated *k*-fold cross-validation, whereby *k* = 10 and repetitions = 100. Performance measures included:

- Area Under the Curve (AUC) – a measure of overall performance that depicts the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR)
- F_1 Score – illustrates the harmonic mean between Positive Predictive Value (PPV) and True Positive Rate (TPR)
- Balanced Error Rate (BER) – the average misclassification error rate of each class
- True Positive Rate (TPR): high anger drive is correctly classified as high anger (sensitivity/recall)
- True Negative Rate (TNR): a low anger drive is correctly classified as low anger (specificity)
- False Positive Rate (FPR): false alarm rate that a low anger drive is misclassified as high anger (type I error)
- False Negative Rate (FNR): a high anger drive has been missed and is misclassified as low anger (type II error)

Figure 4 illustrates that the highest AUC was achieved using both driving and physiological features (73.12%). Solely using physiological features produced comparable results (70.84%), whilst the driving features produced the lowest AUC (67.60%). This pattern continues within the F_1 results as the probability of correctly distinguishing a high anger drive when high instances of anger has actually occurred was highest using driving and physiological features (64.95%) and physiological features (64.40%). <u>However, repeated-measures ANOVAs to test for differences between the models failed to reveal a statistically significant effect using either AUC [$F(2,8) = 3.25$, $p=0.08$] or F_1 [$F(2,8) = 1.31$, $p=0.36$].</u> These datasets produced comparable results, which was in contrast to utilizing only driving features (60.07%). In terms of the misclassification error rate, the driving and physiological features missed the least amount of instance (33.83%), compared to only driving features (36.23%).

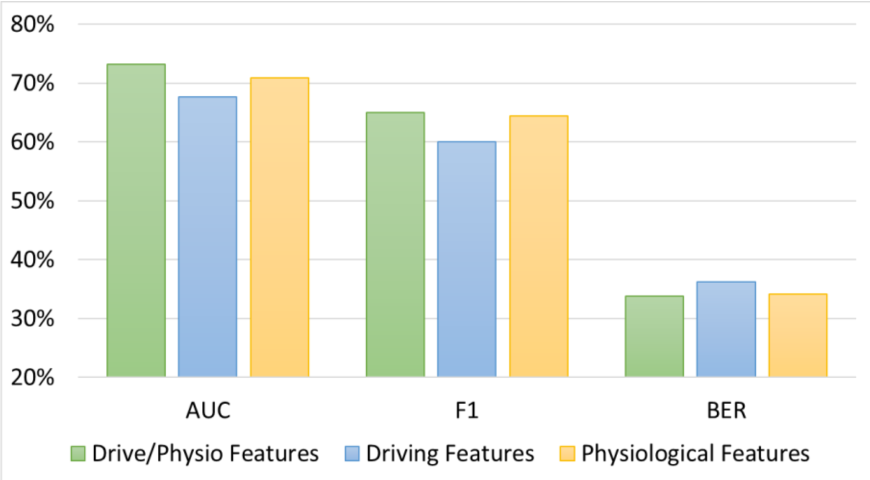


Figure 4. Classifier performance of each dataset of features in terms of Area Under the Curve (AUC), F_1 Score and Balanced Error Rate (BER)

Figure 5 illustrates that the highest TPR of correctly classifying a high anger drive was achieved using both driving and physiological features (64.15%), whilst the lowest FNR of 35.85% was also achieved using this dataset. This finding illustrates that using both physiological and driving features returns results that miss fewer instances of high anger, compared to the other datasets. The TNR results illustrate only marginal differences between the datasets. It seems that detecting low anger drives exhibited the highest accuracy using only the driving features (69.92%), compared to 68.44% using only physiological features and 68.20% using the combined features. The false alarm rate (FPR) results mirror the TNR rates. Using only driving features slightly outperformed the rest at 30.08%, whilst physiological features resulted in a 31.56% false alarm rate and using both driving and physiological features resulted in 31.80%. A repeated-measures MANOVA was performed on True Positive and True Negative rates to test for differences between the three models, this MANOVA revealed no significant differences between the three models [$F(2,8) = 1.81$, $p=0.22$] for overall rate and there was no significant interaction. The same approach was taken to test for differences between the False Positive and False Negative rates, but no significant effects were found [$F(2,8) = 1.14$, $p=0.34$].

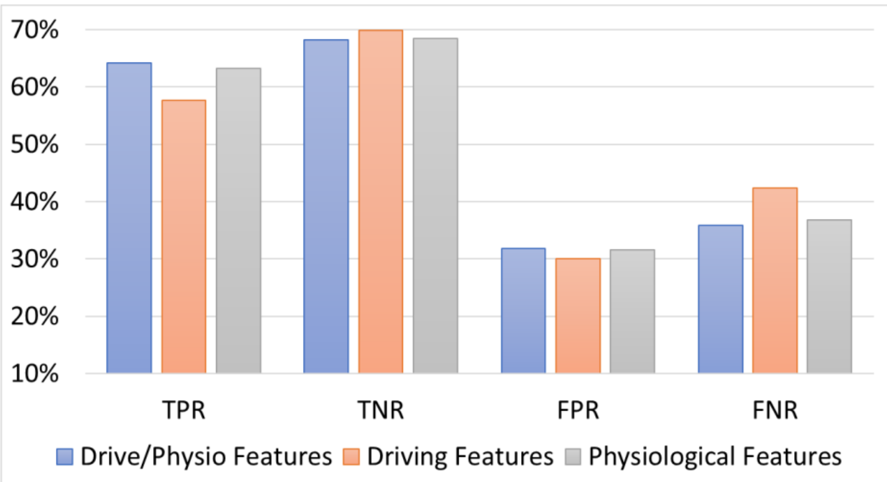


Figure 5. Classifier performance of each dataset of features in terms of True Positive Rate [TPR], True Negative Rate [TNR], False Positive Rate [FPR] and False Negative Rate [FNR]

2.7 Study One Conclusions

The study revealed that: (1) classification via physiology and a combined approach of driving features plus physiology achieved an accuracy rate above 70% (Figure 4), and (2) that physiological features selected for the classification analyses, which were sensitive to the subjective experience of anger, included mean heart rate, power in high frequency component of HRV and PTT. In addition, a combination of measures derived from cardiovascular psychophysiology and driving (e.g. proportion of journey time travelling at less than 10mph) produced the highest classification accuracy, but was not significantly higher than the accuracy obtained from either vehicle parameter or physiology alone.

These findings replicate earlier work (Schaeffer et al, 1988; Stokols et al, 1978) and confirm the existence of meaningful relationship between cardiovascular reactivity and negative emotions due to journey impedance in everyday life. As well as confirming a link between blood pressure and journey impedance (Stokols et al, 1978), study one demonstrated a connection between HF component of HRV and subjective anger, which is particularly important for the current work, given the known relationship between HF HRV and blood-borne markers of inflammation (Cooper et al, 2015). Hence, study one provides supporting evidence that a subjective experience of anger during real-world driving is associated with inflammatory processes at a biological level.

With respect to the logistics of capturing negative emotions during driving, it would be ideal if changes in anger could be inferred on the basis of vehicle parameters alone. An assessment based on implicit changes in speed would be unobtrusive and the data would be easy to obtain. Unfortunately, our classification model based on vehicle parameters alone was the least accurate of the three models tested (Figure 4) and exhibited high false negative rate (

Figure **5**), i.e. anger detected when it was not present – although these differences were not statistically significant when tested. Although it should be noted that the driving dataset was limited specifically to only features related to speed, as well as only focusing on those times when the vehicle was moving slowly.

It is suggested that a dataset that combined features derived from psychophysiology with speed profiles can provide important contextual information for the interpretation of cardiovascular data. For example, our measures of cardiovascular reactivity enabled us to differentiate between those episodes of journey impedance that elevated inflammation and those which did not. The results from this classification also demonstrated a connection between measures of cardiovascular reactivity, which were collected "in the moment", and subjective ratings of anger, which have been captured retrospectively.

On the basis of study one, we can conclude that cardiovascular reactivity is an important indicator of those times and locations when inflammation was elevated during a commuter journey. This insight is important to keep in mind as analyses from study one were used to inform the creation of an interactive data visualization that was developed and tested during study two. Those physiological features that were selected using the RELIEFF algorithm in study one capture different physiological mechanisms that appear to be activated during the experience of anger. For instance, increased heart rate is a general measure of activation of the autonomic system, whilst increased HF_HRV is associated with reduced parasympathetic activity and inflammation; PTT serves as a proxy measure of increased systolic blood pressure, which is also associated with sympathetic activation. By cross-referencing changes in cardiovascular reactivity with vehicle speed, we are able to draw inferences about the causes of driver anger. For example, a sudden reduction of speed and sustained episode of low speed (<10mph) combined with increased heart rate/HF_HRV/PTT would characterise increased inflammation due to stationary traffic. This method of cross-referencing between physiological data and the context of the driving task data was used as the basis for the design of the data visualization in study two.

3 Study Two

3.1 Design of Study

The second study was designed with three distinct phases (see Figure 6): (1) a pre-test period when data were collected during commuter journeys both to and from work on two successive days, (2) a data visualization session where participants were invited to the laboratory to interact with a data visualization based on data collected during the pre-test period, and (3) a post-test period when data were collected during commuter journeys on two successive days following exposure to data visualisation. Hence, the data visualization session (2) functioned as an intervention and short-term changes in cardiovascular activity and subjective mood that emerged during the post-test period (3) were used to index the effectiveness of the data visualization.

Figure 6. Design of study 2 that consisted of three distinct phases: 1) pre-test, 2) data visualization interaction and 3) post-test

The design of the pre-test period was identical to study one. Participants were fitted with the lifelogging platform described earlier in section 2.3; this hardware was supplemented with additional functionality within the smartphone. A custom-built Android application running on the Samsung™ Galaxy S5/S6 smartphone was developed to capture photographs of the forward view of the road, GPS location (latitude/longitude coordinates) and vehicle speed (during study 2 the Shimmer3™ accelerometer unit was replaced with an application to capture speed from the smartphone). Photographs of the forward view were captured every 30 seconds. A mobile phone holder was used to place the smartphone with the camera facing through the front windshield.

After the pre-test period had been completed, apparatus was collected from each participant and data were downloaded into the data visualization interface. Participants were subsequently asked to attend the data visualization session. Instructions on how to interact with the data visualization were provided, the functions of the interface were described and demonstrated. Participants were shown how to use the tabs to investigate different types of data and how to access ‘maps’ for their different journeys. They also received instructions on the use of the mouse to highlight icons on the map and still photographs. In addition to technical instructions, participants received additional information that allowed them to understand the meaning of the cardiovascular data, i.e. heart rate = level of autonomic activation, HRV = inflammation, PTT = blood pressure. No time limit was placed on their interaction with the data visualization and participants were instructed to interact with their data for as long as they wished. After the participants had consulted the data visualization, derived from each of the three variables across four commuter journeys, an interview was performed with participants, which was structured around four questions pertaining to: effects of morning vs. evening driving, locations of high cardiovascular reactivity, design of the interface and utility of the system (see section 3.4 for specific questions). After the data visualization session, data collection commenced on the post-test period. The design of the post-test period of data collection were identical to those described for the pre-test phase. The second study resulted in ~43 hours (159,496,783 instances) of data from the lifelogging platform over the four days of the study. In total across both studies, ~106 hours (525, 697,711 instances) of raw data were collected.

3.2 Participants

The participant sample included eight individuals – six females and two males, with an age range from 28 to 57 years (mean = 39.50, SD = 11.10). None of the sample had any history of heart disease or were taking medication that would influence cardiovascular activity. All protocols for recruitment and data collection were approved by the institutional Research Ethics Committee prior to commencement of data collection.

3.3 Experimental Measures

The signal processing procedures used to pre-process the physiological data were identical to those utilised in study one. Time and frequency domain features were extracted from the physiological data (HR, HF_HRV, PTT) on the basis of 30 sec time windows, which was identical to quantifications used in study one. Vehicle speed was captured in metres per second (m/s) (i.e. velocity) on the basis of location. Features related to the context of the drive were visually scored from the photographs to deliver measures of: traffic density (number of vehicles visible through the forward view), time of day (e.g. earlier than 9am, 9am-12pm, 12pm-5pm, after 5pm), road type (number of lanes), presence of traffic lights (yes/no), slow moving traffic travelling at <10mph (yes/no), at roundabout (yes/no), road type (e.g. inner city, town/village, rural, tunnel) and weather (e.g. Clear Day/Sunny, Raining Day, Raining Dark (Night), Cloudy/Overcast Day, Night (Dark), Snow/Ice Day, Snow/Ice Dark (Night), Fog Day, Fog Dark (Night), Clear Evening, Clear Dawn).

During the second study, subjective self-reported mood was assessed via the UWIST Mood Adjective Checklist (UMACL) (Matthews et al, 1990). This questionnaire has three major dimensions: energetical arousal (alert vs. tired), tense arousal (anxious vs. relaxed) and hedonic tone (happy vs. sad). Participants were required to rate how well each word described their current mood *at this moment* state on a Likert scale, whereby 1 = *definitely*, 2= *slightly*, 3 = *slightly not* and 4 = *definitely not*. Participants completed the questionnaires before and after each journey and a change score was calculated (after – before) to index changes in mood for all three scales due to the journey. The questionnaire were administered using a custom-built Android application that was running on the administered Samsung™ Galaxy S5/S6 smartphone.

3.4 Data Visualisation Interface

The interactive data visualization has been developed as an online tool for participants to reflect on their cardiovascular and driving data. It was decided to design the interface upon a geospatial framework as the use of location is a common framework for lifelogging systems that seek to associate instances of stress with a specific place (Bauer and Lukowicz, 2012; Sano and Picard, 2013; Likamwa et al., 2013; Vhaduri et al., 2014; Bogomolov et al., 2014; Maier et al., 2014; Jaques et al., 2015; Sarker et al., 2016). It has been demonstrated that human activity and mood can be inferred using multimodal smartphone sensor streams, including location, which provides an opportunity for the user to discover patterns of stress in everyday life (Bauer & Lukowicz, 2012; Bogomolov et al, 2014; Jaques et al, 2015; Sano & Picard, 2013; Sarker et al, 2016). In addition, to framing the data within a geospatial framework, it was important for our system to trigger memory recall in order to provoke periods of reflection, i.e. for users to understand which aspect of the traffic environment had prompted a negative emotion. The decision to incorporate 'snapshots' based on a camera placed in the forward view of the vehicle into the design of the interface was taken to promote recall and inspired by earlier work; for example, the lifelogging system developed by Kalnikaite et al (2010) demonstrated that visual images promoted detailed recollection and they argued that augmenting lifelogging images with geographic data supported self-referential processes that allow participants to reconstruct their own behaviour. The design for our system was inspired by these earlier works, which used a geographical interface metaphor, together with still images and visualisations of cardiovascular data.

On the basis of the analysis of study 1, cardiovascular variables found to be predictive of subjective anger triggered by slow traffic were included in the visualization. The resulting interface design (see illustration in Figure 7) contains three data visualizations that pertain to HR, PTT and HRV, which are displayed on separate web pages. Each page is composed of four elements:

1. Tabs at the top of the page move the participant between the three different visualization web pages (HR, PTT and HRV)
2. A Google™ map that displays colour-coded markers of the driver's route to and from work
3. When the participant clicks on a marker on the map, an information window opens that contains the associated photograph and speed of that time
4. An interactive bar chart at the bottom of the page plots time against speed of the entire journey. Hovering the mouse over bars within the chart displays the traffic density of the associated time

The synchronized data was encoded in JSON (JavaScript Object Notation), whereby each object contained a comma-separated list of name/value pairs that were related to the drive. For each timestamp, the associated latitude, longitude, speed, photo, traffic density (car count), HR, PTT and HRV were recorded. Using the JSON data, custom-made colour-coded markers were placed on the map using the latitude and longitude GPS coordinates. For *each* drive, the 25th, 50th and 75th percentiles of the HR, PTT and HRV data were calculated. Each marker on the associated map was colour-coded based on these statistics. For instance, in relation to the heart rate map, instances where the heart rate data was:

- Below the 25th percentile was coded green
- Between 25th and 50th percentile was coded yellow
- Between 50th and 75th percentile was coded pink
- Above 75th percentile was coded red

The photographs and speed data were then linked to each marker via the timestamp. When a marker is clicked, an information window opens to display the associated photograph and speed at that time window. The bar chart underneath the map is used to depict the distribution of speed across the entire journey. When the mouse is placed over a bar in the chart, traffic density of that time is displayed above the bar.

When a participant moves across to the PTT and HRV pages, they are presented with the same display of the map with location markers, photographs, speed and bar chart. However, as PTT and HRV are the inverse of heart rate (i.e. low PTT/HRV is a sign of inflammation) the marker colours within these two pages were coded differently than the heart rate page. As such, the PTT and HRV maps were colour-coded in reverse, whereby instances that were:

- Below the 25th percentile was coded red
- Between 25th and 50th percentile was coded pink
- Between 50th and 75th percentile was coded yellow
- Above 75th percentile was coded green

<u>The purpose of the interactive visualization was to provide context to cardiovascular activity by enabling participants to freely explore their data in a variety of ways. For instance, the map can be used to explore their data in relation to location; e.g. particular coloured markers can be investigated to indicate locations of these occurrences, as well as the associated speed and photographs. Alternatively, the bar chart can be used to explore their data in relation to speed; e.g. times where speed was particularly low can be investigated further to illustrate traffic density, as well as linking to the map to display location and a photograph.</u>

The benefit of the visualization is that it is *personalized* to the *individual* and the specific *drive*. This is because each marker's colour is based on cardiovascular data pertaining to only that drive, which makes each map unique. In total, 12 maps were generated per participant (one HR, PTT and HRV per morning and evening drive over 2 days).

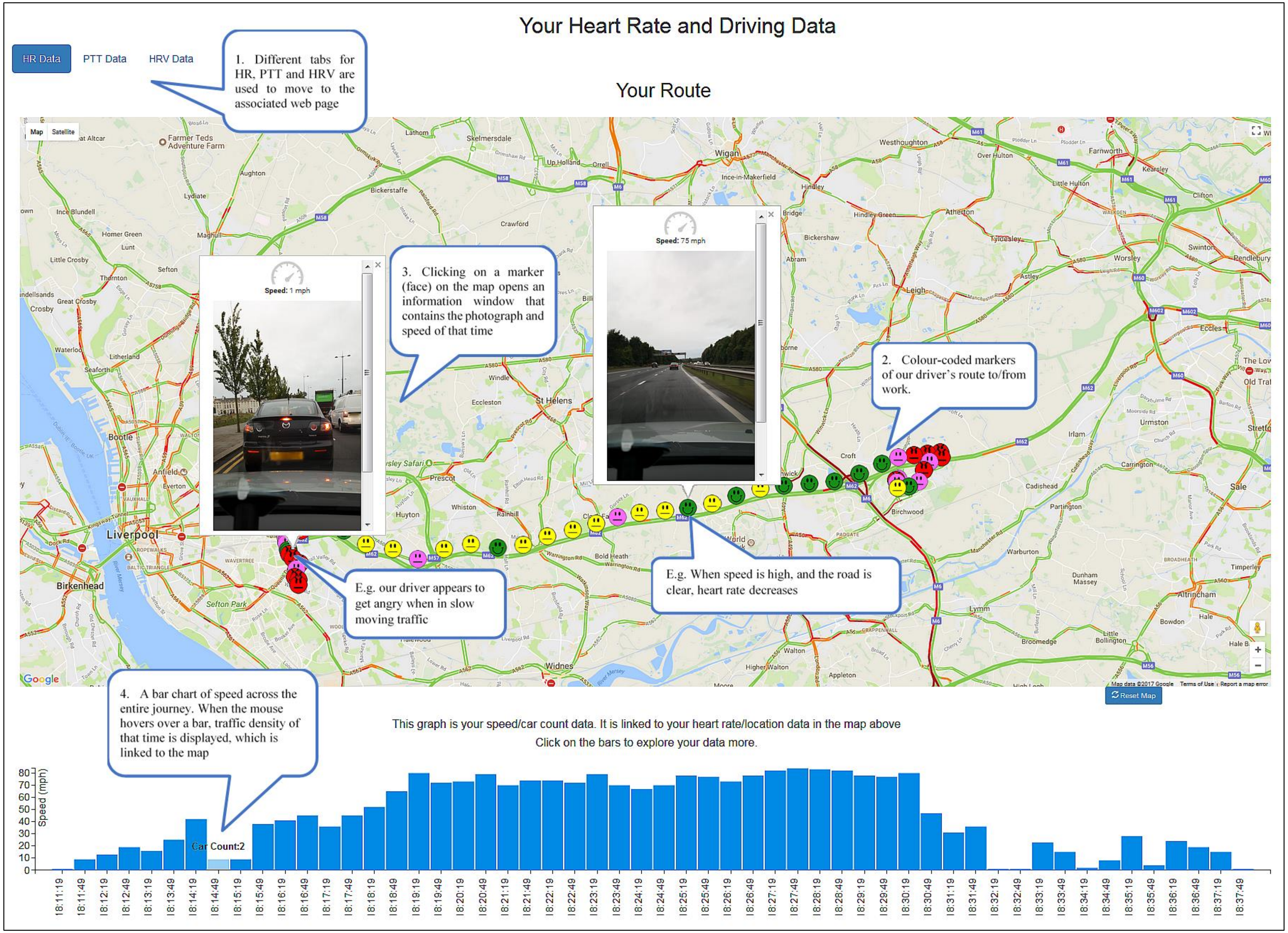


Figure 7. Data visualization that links cardiovascular psychophysiology to an interactive map that is linked to location, photos, speed and traffic density

Following exposure to the data visualization, participants were asked a number of open questions in an interview format. Immediately after their interaction with the data visualization derived from heart rate, PTT and HRV, they were asked the following questions in all three cases:

(1) Did [cardiovascular parameter] seem higher on journeys in the morning to work or in the evening from work?

(2) Can you see any pattern when your [cardiovascular parameter] is red? Does it happen in certain places or parts of the journey? If it does, why do you think that is?

These questions that pertained to each data visualization (e.g. HR, PTT, HRV) were complimented by general questions, which were:

(3) What do you think of this data visualization of heart activity in everyday life? Is it interesting and useful or do you find it worrying and intrusive or do you simply think it's unnecessary and unhelpful?

(4) If a convenient version of the sensors you used were available in the future, say built into your clothes or the seatbelt, and you could easily peruse the data on your phone, is that something that you would use?

3.5 Study 2 Results

The purpose of the second study was to assess whether cardiovascular reactivity was attenuated in a negative driving scenario due to their exposure to the data visualization. For consistency, it was decided to focus on journey impedance and on the physiological measures that were used in the classification results of study one (section 2.6). Three categories of data were collected during study 2: cardiovascular data, self-reported mood and subjective comments with respect to the data visualisation (via participant interviews). Cardiovascular and mood data were collected from two journeys per day (morning vs. afternoon) over two days prior to interaction with the data visualization; these data are called *pre-test*. The same data were subsequently gathered on a *post-test* basis during the four journeys over the two days that followed participants' interaction with the data visualization.

3.5.1 Cardiovascular Data Results

The purpose of the data visualization was to represent changes in cardiovascular activity when drivers experienced some degree of journey impedance. Cardiovascular data were extracted from each journey for epochs associated with journey impedance, i.e. speed fell below 10 mph (16 km/h) and mean values for *pre-test* and *post-test* cardiovascular data for those epochs were calculated for HR, HF_HRV and PTT. These variables were subjected to analyses using 2 (pre-, post-test) x 2 (morning, afternoon) ANOVA. Descriptive statistics are represented in Table 1.

Table 1. Means and standard deviations for Cardiovascular Data for Pre- vs. Post-Test Journeys.

Variable	Pre-Test	Post-Test	Sig.
Heart Rate *(bpm)*	82.94 [2.87]	77.54 [3.45]	.01
HF_HRV *(ms^2)*	148.64 [7.84]	151.10 [6.85]	.01
PTT *(ms)*	565.87 [28.78]	553.43 [25.64]	.ns

The analysis of heart rate data revealed significant effects for test [F(1,7)=11.75, p=.01, η^2=0.63] and time of day [F(1,7)=5.05, p=.05, η^2=0.42]. Heart rate was significantly reduced during the post-test period (see Table 1); in addition, HR was higher during the afternoon (M=82.85, s.d.=3.14) compared to the morning commute (M=77.63, s.d.=3.43). The analysis of power in the high-frequency band (HF_HRV) revealed a significant main effect for pre/post-test [F(1,7)=10.43, p=.01, η^2=0.60] and the time of the journey [F(1,7)=8.95, p=.02, η^2=0.56]. Power in the high-frequency band was significantly higher during the post-test compared to pre-test period (see Table 1); in addition, HF_HRV mean power was significantly lower in the morning (M=346.54, s.d.=22.17) compared to the afternoon (M=307.98, s.d.=19.6). The analysis of PTT revealed no significant differences for either pre/post-test [F(1,7)=0.19, p=.68] or time of day [F(1,7)=0.58, p=.47].

3.5.2 Self-Reported Mood

The UMACL questionnaire yielded three measures of mood: Energetical Arousal (EA: active vs. fatigued), Tense Arousal (TA: anxious vs. relaxed) and Hedonic Tone (HT: happy vs. sad). Each measure was captured before and after each commuter journey and converted into a change score, i.e. post-drive score minus pre-drive score, yielding a single measure for each journey, where a positive number was equated with an increase in that component of mood over the course of the journey. These change scores were subjected to the 2 (pre/post-test) x 2 (morning, afternoon) ANOVA model used to analyse cardiovascular data.

The analysis of EA revealed no significant effect between pre- and post-test [F(1,7)=0.01, p=.95], however feelings of alertness were significantly increased after the afternoon journey (M=-1.03, s.d.=1.47) compared to the morning journey (M=0.00, s.d.=1.13) [F(1,7)=7.88, p=.03, η^2=0.53]. No significant main effects were observed with respect to Tense Arousal with respect to either pre/post-test [F(1,7)=0.86, p=.39] or morning vs afternoon [F(1,7)=1.94, p=.21]. The analysis of Hedonic Tone also failed to reveal any significant difference between pre- and post-test periods [F(1,7)=0.65, p=.45] or morning vs. afternoon [F(1,7)=0.38, p=.55].

3.5.3 Interviews

Once participants had interacted with the data visualization, they were asked a number of open questions in an interview format (as described in section 3.4 above). For example, participants were asked "*can you see any pattern when your [cardiovascular parameter] is red? Does it happen in certain places or parts of the journey? If it does, why do you think that is?*" This question was presented to participants on three occasions after they viewed data visualisation pertaining to HR, PTT and HRV respectively. All verbal answers were clustered into common themes and are reported in Table 2.

Table 2. Participants' Explanations for High HR, Low PTT and Low HRV After Viewing Data Visualization Interface. Note: number in brackets in the Theme column denotes number of comments on this Theme.

Theme	Examples
Journey Impedance (7)	*"traffic was high and slow-moving"* *"stuck in traffic"* *"restrictive speed limits"*
Mental Workload (8)	*"complexity of decision-making"*

	"high speed driving" *"high traffic density"*
Errors (3)	*"Thought I jumped a red light"* *"Took corner at too high speed"*
Aggression (2)	*"Got cut up by another driver"* *"Got angry with another driver"*
Rumination (2)	*"anxious about something that happened earlier"* *"a negative situation to think about"*

Participants were also asked a number of general questions about the data visualization. Question 3 ("*What do you think of this data visualisation of heart activity in everyday life? Is it interesting and useful or do you find it worrying and intrusive or do you simply think it's unnecessary and unhelpful?*") elicited several positive and negative responses, a sample of which are reproduced below in Table 3.

Table 3. Participants' Responses to Question 3

"it was a little too detailed. Photographs provided good context. It would be more useful if you could act on it, so calibrate for a person then allow real-time feedback in a simple non-intrusive way." *"It was very interesting to see the patterns and at what point I was angry. I found it to be very interesting and useful. The photos made it easy to see exactly what's going on..."* *"Interesting and useful, it makes you aware of the variability, seeing the physiological impact was useful."* *"Interesting to see variability, it would have been useful to have absolute values to compare between drives."* *"Interesting and worrying. This is a regular activity and obviously I was not as relaxed as I thought I was."* *"I think the system is more relevant for longer journeys and long-distance driving. It was interesting because it showed scientific data in a personalised way."*

The final question of the interview asked participants "*if a convenient version of the sensors you used were available in the future, say built into your clothes or the seatbelt, and you could easily peruse the data on your phone, is that something that you would use?*" A selection of their responses to this question is presented in Table

4 below.

Table 4. Participants' Responses to Question 4

"*Yes, probably, but not sure about long-term use. Would need a short-term reason to use it, all depends on the end-goal, there is the potential for hypochondria.*"
"Yes, to review and reflect on the day, but useful outside driving, for anxiety disorders."
"For driving, no. would only use for exercise activity."
"I thought the utility was questionable, seeing feedback would be better when you were driving then you could adapt."
"Would use it because I like gadgets especially for longer journeys, could be useful for people with health problems to assess impact of everyday life."
"…if illness was experienced then it may be useful to monitor your mood to reduce stress. Another concern is that the data itself may be used by insurance companies."
"Possibly would use it. It would help me to understand any anger issues associated with my driving."

4 Discussion

The goals of the studies were to: (1) inform the development of the data visualisation by utilising physiological variables that were associated with anger during commuter driving, (2) generate an interactive data visualisation that represented cardiovascular reactivity in everyday life, which was easy to interpret and raised awareness of negative emotions and underlying physiological activity, and (3) investigate the impact of interaction with this data visualisation on subsequent emotion and psychophysiological responses.

The investigation into types of features that contributed to a higher level of anger detection (study one) indicated the highest classification rates for multimodal data capture during classification of high vs. low anger. However, differences between in classification accuracy between three models (physiology, vehicle parameters, combined) failed to reach statistical significance. In addition, it was noted that physiological features selected for classification using the RELIEFF algorithm encompassed a range of physiological changes, including pulse transit time (PTT), which is associated with blood pressure (Gesche et al, 2012), and heart rate variability (HRV), which is associated with inflammation (Cooper et al, 2015).

The results of study one analyses were used to inform the design of the interactive data visualisation during the second study. Those physiological features selected for inclusion in the classification model were associated with the experience of negative emotion, i.e. anger. Therefore, the data visualisation encompassed measures of mean heart rate (autonomic activation), HF_HRV (inflammation) and PTT (systolic blood pressure). There was some overlap between the patterns of activity observed across all three variables, but we decided to construct an interface with several tabs (Figure 7) that allowed participants to peruse each set of data in turn. Secondly, because these physiological data are quantitative and sampled at relatively high frequency, there was a risk of the user being overwhelmed by the quantity and complexity of the data. Therefore, we designed a simplified representation of each data set, splitting the data into four percentile bands that could be colour-coded in an intuitive way. The primary motivation for users of the data visualisation was identical to the experimenters in study one, i.e. we wished to identify those instances of increased cardiovascular reactivity and inflammation that occurred over the course of the journey. By labelling those instances clearly (red icons), participants were able to identify and interrogate those instances in order to make an inference about why physiological activity increased at those points. Given that superior classification performance was achieved when physiology and driving parameters were combined in study one, we adopted an approach to designing the data visualisation (see Figure 7) where vehicle parameters (i.e. the bar chart at the bottom of the interface) and geolocated data (the position of the vehicle during that epoch) provided a navigable context for the journey as a whole. When users required additional detail, i.e. episodes of high heart rate, low HF_HRV and low PTT were identified, the interface permitted further investigation of those episodes with reference to vehicle location, a still image of the driving scenario and vehicle speed (Figure 7).

With respect to the results from study two, the absence of any significant effects of data visualisation on subjective mood was unexpected, it was hypothesised that subjective anxiety and negative valence would be reduced during the post-test period due to higher awareness and adaptive strategies of self-regulation. However, this expectation may have been overly simplistic. While it is logical to expect interaction with the data visualisation to enhance awareness of negative emotional states, it does not necessarily follow that increased awareness (of negative emotions) automatically leads to effective strategies for self-regulation. In addition, changes in subjective mood were only captured on a pre- and post-journey basis, as it would have been disruptive and possibly dangerous to elicit regular episodes of subjective self-assessment during the driving task. Hence, only one data point (post- minus pre-journey change score) was obtained per drive for subjective mood, which was insensitive to transient influences on mood during driving, such as: congestion, complex junctions etc. The measurement of mood in context (as a response to a specific trigger in the driving environment) would have been a more sensitive test of our hypotheses, but this level of fidelity was impossible to achieve in real-time.

By contrast, the analyses of cardiovascular data before and after exposure to the data visualisation revealed a number of statistically significant effects between pre- and post-test periods. Because cardiovascular data were available continuously, we cross-referenced these data with vehicle speed and selected only those epochs when drivers experienced slow-moving traffic (<10 mph). This method of filtering the data was far from perfect, i.e. participants may be travelling at slow speed because they were approaching a complex junction or a traffic light; however, we were confident that episodes of traffic congestion would be captured by using this simple criterion, because all the drivers had to enter and leave a busy city location at rush-hour times. The analyses of cardiovascular data revealed that heart rate significantly declined and the high-frequency component of HRV significantly increased when participants experienced slow-moving traffic during the post-test compared to pre-test period (Table 1). The increase of high-frequency HRV is indicative of elevated vagal tone (Porges, 1995) and the observed decrease of heart rate is also consistent with this interpretation. These changes suggested that cardiovascular reactivity to slow-moving traffic was moderated as a result of exposure to the data visualisation. However, the actual mechanism underpinning this finding remains open to interpretation. Participants may have adopted a different psychological coping strategy when they encountered journey impedance, such as acceptance, which has been associated with increased vagal tone (Balzarotti et al, 2017). When participants were asked what had been learned from the data visualisation, a number reported psychological insights, such as being “reactive” or “not in control”, which may have prompted a change in coping strategy, i.e. several comments in Table 3 pointed towards concerns over the level of physiological reactivity revealed by the data visualisation. Alternatively, participants may have actively practiced a psychophysiological mode of self-regulation, such as slow/deep breathing, which would also reduce heart rate and increase vagal tone (Van Diest et al, 2014). The pattern observed in study 2 suggests a change in respiratory patterns because heart rate and high-frequency HRV are particularly sensitive to change in respiratory activity; it should also be noted that no equivalent changes were observed for PTT (Table 1), which would not be strongly influenced by changes in breathing. Participants may have adopted a pattern of slow/deep breathing when experiencing journey impedance, implicitly or as an active attempt to self-regulate cardiovascular reactivity.

It is difficult to identify which specific facet of the data visualisation interface prompted those alterations in cardiovascular psychophysiology observed between the pre- and post-test phases of study two. It is also possible changes in physiological responses represented the participants’ integration of location, still images and multimodal data streams from the visualisation. Feedback from the data visualisation may have been a powerful motivation to actively self-regulate the experience of stress during journey impedance; it was obvious from the interview data (Table 2) that participants identified congestion as a frequent trigger for episodes of increased cardiovascular reactivity. As an additional source of concern and motivation, a number of interview comments focused on the physiological impact of driving on personal health (Table 3) and how an emphasis on high reactivity (red icons on the map) prompted a focus on those physiological “costs” of negative emotion during driving. The whole rationale of the data visualisation was intended to bring these “hidden” patterns of physiological activity to light that accompany stress in everyday life and occur outside the awareness of the individual (Brosschot et al, 2010). One goal of the data visualisation was to provide an opportunity to directly observe these processes, which was unique and informative for our participants. Alternatively, the interview process associated with the data visualisation may have played a direct role in those cardiovascular changes that we observed between pre- and post-test periods, as the questions used in the interview process forced each participant to reflect upon the data visualisation in order to identify triggers for changes in cardiovascular reactivity. As part of the interview process and to aid interpretation of the data visualisation, participants were informed about those physiological inferences that could be drawn from individual cardiovascular markers, e.g. HRV is associated with inflammation in the body, PTT is associated with blood pressure; hence, our participants were capable of reflecting upon the data visualisation from an informed position. This type of explicit link between physiological markers that were visualised on the map and an awareness of the implications for long-term health may have constituted a powerful agent for behaviour change.

There was evidence of increased awareness of emotional triggers from the interview data and altered psychophysiological reactivity during journey impedance; however, the absence of any data collection after the post-test phase, such as a follow-up questionnaire or interviews, made it difficult to assess whether observed changes stemmed from a conscious or unconscious process of self-regulation. It would be valuable to explore this particular issue and identify coping strategies for self-regulation of negative states via further research. As an additional caveat, the post-test phase immediately followed the data visualisation session and only lasted for two days, which prompts the question of whether those observed changes in cardiovascular reactivity would persist a week or a month later.

With respect to the data visualisation interface, participants were able to easily interrogate personal data and extract meaningful information. The inclusion of context-specific photographs was enormously useful for participants to identify specific triggers for cardiovascular change. In general, participants found the combination of colour-coded icons placed on the Google map easy to understand. However, several participants requested a dynamic 'playback' mode and a colour-coding system that was based upon absolute rather than relative scores, which would permit comparisons between different journeys. The bar chart, which provided an indication of car counts/traffic density, was not deemed to be very useful and could have been omitted. Despite positive responses to the data visualisation, it was noted that several participants questioned the utility of this approach in the context of everyday driving. The general feeling (Table 4) was that real-time feedback would have been more useful in aiding active self-regulation in situ compared to the retrospective approach that we used in the current study. In addition, a number of participants felt the approach was only really warranted for users with existing medical conditions.

The second study contained a number of shortcomings and weaknesses. A large volume of data was collected over four days of driving but the number of individual participants was low. This weakness represented the practical difficulty of asking individuals to accommodate the data collection and associated inconvenience into their daily routines. While the Shimmer sensors provided excellent data fidelity and it was important for the study to obtain an ECG, our participants found the necessary set-up of apparatus to be burdensome. There are alternative methods for monitoring heart rate and HRV non-invasively (Kranjec et al, 2014) and it is possible to capture HRV from a PPG signal if the participant remains in a stationary position (Lin et al, 2014). By reducing the logistic burden of data collection on participants, it would be possible to employ a similar protocol with a higher number of participants. The duration of the measurement period was limited by similar factors and it would have been preferable to monitor psychophysiology and mood over a longer period of time, simply to assess whether short-term changes observed in the study persisted over weeks rather than days; this longitudinal methodology would also permit repeated interaction with the data visualisation interface and the inclusion of follow-up questionnaires. If a larger pool of participants was available, a follow-up study could also include a between-groups experimental design, wherein one group received data visualisation and the second (control) group did not. The current study used photographs taken every 30 seconds in order to provide a visual documentation of each journey. This approach ran a risk of missing transient events on the road, e.g. sudden braking of lead vehicle, erratic behaviour from another motorist, and it could be argued that film footage would improve the visual documentation because it provides a continuous record of events on the road. One can imagine an alternative data visualisation wherein clicking on a red marker within the map prompts a short playback on a second-by-second basis with accompanying psychophysiological data record. However, this approach would be time intensive to review and there is a trade-off between the fidelity of the data record and the willingness of the user to review frequent daily activities at that level of detail.

With respect to future work, it would be useful to compare and contrast real-time feedback of negative emotional states with the retrospective record provided in the current study. It can be argued that real-time feedback would be a superior approach to emotion regulation, because it works in situ and provides timely feedback, but introduction of real-time emotional feedback during driving. A number of researchers have experimented with ambient light as feedback to driver mood and psychological states (Hassib et al, 2019), the use of emoticons (Kim & Lee, 2015) and the design of a dashboard dedicated to feedback on driver state (Völkel et al, 2018). Irrespective of the design of the feedback interface, there are the risks of distraction inadvertently intensifying negative emotional states when the person is driving. With respect to retrospective feedback, such as the interface designed in the current study, one can imagine a minimalist design where icons or pins are dropped into an electronic map of a regular route only to alert individuals of specific 'hot points' for negative emotions. The current study collected physiological data for individual drivers travelling on different roads at different times of day. Future work could adopt a 'big data' approach where physiology is monitored across a large group of drivers, travelling on the same road network at the same time. The resulting data could provide valuable insight into health epidemiology (i.e. assessing cardiovascular changes during driving as a marker for disease), traffic management (i.e. understanding the relationship between traffic flow and driver physiology) and roadway design (i.e. identifying junctions or stretches of road that are associated with high levels of cardiovascular reactivity for a large group of drivers). It would also be valuable to use this type of lifelogging platform to assess different methods of self-regulation in everyday life with respect to the reduction of inflammation. Different types of self-regulatory activity, such as slow breathing or psychological acceptance, could be contrasted and feedback via data visualisations, such as the one used in the current study, could play an important role as a training tool. The type of monitoring used in the study could also be used as an input to a passive or ambient intervention, e.g. detection of cardiovascular reactivity could prompt the introduction of low activation music, which has been shown to be effective in the reduction of systolic blood pressure during journey impedance (Fairclough et al, 2014).

5 Conclusion

The paper describes research into the development of a lifelogging system designed to capture negative emotions and cardiovascular activity during commuter driving and present interactive feedback to users. The first study demonstrated that features derived from psychophysiology and driving behaviour could be used to classify instances of high vs. low anger based upon subjective self-assessment. This study led to the development of an interactive data visualization wherein cardiovascular data and measures of driving were integrated and presented in a geo-located format. Participants found the data visualization easy to understand and were able to draw inferences about the links between driving activity and physiological changes. Participants identified increased mental workload and journey impedance as the two most common triggers for increased cardiovascular reactivity. There was no evidence for any effect on subjective mood either with respect to increased emotional awareness or adaptive coping. However, heart rate was found to decline and high frequency HRV increased when participants encountered slow-moving traffic as a direct result of interacting with the data visualization. The specificity of the effect on cardiovascular parameter suggests that participants either consciously or unconsciously altered breathing activity during traffic congestion.

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