



Detection of social connectedness in everyday life via multimodal lifelogging data

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ABSTRACT

Loneliness, low mood, and social disconnection can have damaging effects on physical and mental health. Detecting these emotions in the context of everyday life is important as these psychological states can manifest differently outside the laboratory. Lifelogging and quantified self technologies, including wearable devices, offer an approach to continuously monitor physiological signals in the real-world. However, little work has been undertaken with these devices to detect social connection in everyday life. This paper presents a study that leveraged machine learning to infer mood and social connectedness in everyday life using multimodal lifelogging data collected via a wrist-worn wearable device. Fifty participants were supplied with a wearable device and smartphone that collected physiological and subjective data across two consecutive weekdays as they went about their daily lives. The analysis examined physiological correlates between a person's psychological perceptions of general connectedness, as well as feelings of in-the-moment social connection to people within an estimated 5 m vicinity and mood at specific timepoints using four machine learning classification models – k-Nearest Neighbour, Random Forest, Support Vector Machine and Naïve Bayes. Results demonstrated that Random Forest obtained the highest accuracy of 0.8 – 0.84 for the binary detection of mood and social connection in everyday life.

1. Introduction

Loneliness is a societal problem affecting all age groups, but particularly young people (15 – 25 years old), who are transitioning to adulthood, and older adults (75 years and above), who experience later life transitions (e.g., bereavement). On the other hand, research shows that people who have multiple, positive social connections are healthier, happier, and live longer (Li and Xia, 2020). The effects of social disconnection on mortality are equivalent to heavy smoking and stronger than well-known predictors, such as physical inactivity, obesity, and alcohol use (Holt-Lunstad et al., 2010). Social disconnection influences many disease processes and is a major risk factor for multiple illnesses — increasing the risk of coronary heart disease (CHD) by 29 % and stroke by 32 % (Valtorta et al., 2016). Psychological processes of mood and emotion — especially psychological distress — are often associated with feelings of disconnectedness, which are in turn

associated with loneliness (Uchino, 2006). The negative emotions and stresses experienced in the context of chronic loneliness can contribute to high blood pressure and cardiovascular disease (CVD), including CHD and in turn increase the risk of disability and chronic disease (Li and Xia, 2020; Rokach and Patel, 2024). There is also evidence of the vital role that positive social engagement plays in improving the mental and metabolic health of adolescents (Goosby et al., 2013), reducing the development of dementia (Bennett et al., 2006), physical frailty (Gale et al., 2018), and autonomic, endocrine, and immune function decline in chronic disease (Hawkey and Cacioppo, 2003).

The area of self-tracking, also known as the quantified self or lifelogging, refers to the idea of obtaining personal insight through numerical data, which is often objective and collected using sensing devices (Schueller et al., 2021). Lifelogging technologies provide a particularly useful application to understand the links between physiology and psychological states in everyday life, and they can be used to

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both assess and manage the effects of disconnection. Lifelogging is defined by a process of continuous quantification and self-tracking, which works by “*recording physiological as well as behavioral (activity) data and stor[ing] them for knowledge extraction at a later stage, which allows self-archiving, self-observation and self-reflection*” (Climent-Pérez et al., 2020, p.2). This process of self-tracking and self-quantification is often undertaken using non-intrusive technologies, such as wearable and mobile devices (Climent-Pérez et al., 2020).

The measurement of complex psychological processes (including perceptions of social connection and mood) often occurs in laboratories, where those processes can be manipulated under controlled conditions. Yet, the resulting data may not accurately represent the real-world due to the artificial nature of these environments (Albertetti et al., 2020). Collecting data in real-world contexts offers greater ecological validity, but detecting psychological processes and states in everyday life presents researchers with several challenges. For instance, in everyday life, ground truth data must be periodically collected, usually through subjective self-report surveys, to provide a label for concurrent data from physiology or behaviour (Can et al., 2019). Although they [self-reports] are relatively straightforward to administer, they can be burdensome to complete particularly in studies such as this where repeated data collection is required — resulting in low adherence. They can also be influenced by recollection and reporting bias (e.g., reflecting social desirability or gender) (Areal et al., 2016; Can et al., 2020; Harley, 2016; Krumpal, 2013; Liapis et al., 2015). For instance, in conforming to social norms participants may answer questions to represent themselves positively, in ways that do not reflect their actual behaviours (Krumpal, 2013). Additionally, inaccuracies and recollection/reporting bias can occur if participants construe an emotional adjective differently from the researcher, if they have not experienced the emotion that they are required to report on before, or if they cannot accurately remember the emotion and time that they felt it (Harley, 2016). These limitations can be mitigated by cross-referencing self-reports with objective physiological data collected via wearable devices (Can et al., 2020).

1.1. Novelty and contributions

The aim of this research is to detect mood and social connectedness in everyday life via machine learning algorithms using multimodal lifelogging data that has been collected using a wearable wrist-worn device. As such, the novelty of the work is in the detection of experienced mood-related social connectedness using wearable sensing of physiological measures, as well as insights into social connectedness and loneliness using lifelogging technology.

The identification of objective physiological correlates of social disconnection has not been undertaken before under real-world conditions. As such, this study provides two important contributions. Firstly, we detected mood-related trait social connectedness (i.e. general feelings of social connection, energetic arousal, and hedonic tone) with a reasonable degree of accuracy. Secondly, we developed a social density estimation model of people within a 5 m vicinity of participants and detected social connectedness to those people (state social connectedness) with a high degree of accuracy. Together, this provides us with models that are able to detect intricate psychological states using physiological features from wearable devices that represent activity of the Autonomous Nervous System (ANS) that are important correlates of social connection and mood (Bosle et al., 2022; Dissanayake et al., 2022; Kreibig, 2010). We are unaware of any other studies that have utilized only physiological data to detect feelings of social connection in these ways (i.e. both generally and to others in the vicinity). Overall, our results demonstrate that complex social emotions can be detected in everyday life using physiological data, which provides greater ecological validity of the results.

The rest of the paper is organised as follows. The next section discusses related work in the areas of emotion and social connectedness (Section 2). This is followed by a description of the study that includes

details of the data collection system, procedure, experimental measures, and data processing pipeline. This section also includes details of the data analysis procedure, including the methodology for labelling the data, and details of the classification pipeline that has been implemented (Section 3). We then describe the results (Section 4), and discuss findings, implications, limitations and directions for future work (Section 5) before the paper is concluded (Section 6).

2. Related work

Mobile and wearable sensing technologies have the potential to support the detection of emotions in ways that can promote improvement in (mental) health and wellbeing (Nepal et al., 2024; Stuyck et al., 2022). Smartphones and wearable devices incorporate various sensors capable of capturing a range of physiological signals (e.g., heart rate) as well as contextual data (e.g., related to activity and location). This multimodal approach allows researchers to gather multiple streams of data, which can be subsequently amalgamated into a comprehensive record of self-tracking and quantified-self data.

2.1. Definitions

2.1.1. Mood

Mood can be interpreted in multiple ways and is a term that is often used analogously with other phrases, including emotion and affect (Kreibig, 2010; Meegahapola et al., 2022). Mood often refers to immediate affective experiences, but this can vary between fleeting emotional states and longer-lasting traits (Boyle et al., 2015; Stolarski and Matthews, 2016). This paper uses Russell’s (1980) two-dimensional Circumplex Model of Affect (see Fig. 1) as a basis to measure mood states. This is an influential model, which posits that dimensions of affective states are interrelated and occur because of two neurophysiological systems — Valence and Arousal — with each ranging from positive to negative (Opoku Asare et al., 2022; Posner et al., 2005; Samuel et al., 2019). Valence refers to pleasure–displeasure and is indicative of the positive or negative disposition of affect, whilst arousal refers to alertness and signifies the extent of the intensity of affect, which ranges from high (active) to low (passive) (Posner et al., 2005; Samuel et al., 2019). This paper used the model as a basis to measure mood states.

2.1.2. Social connectedness and mood-related social connectedness

Social connection is a pillar of human existence; being connected socially to people is critical for our physical and mental health and wellbeing and decreases all-cause mortality (Lamblin et al., 2017;

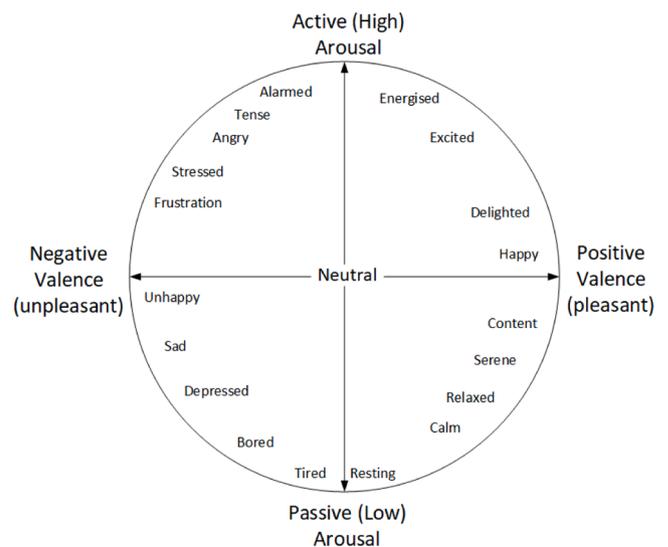


Fig. 1. Circumplex Model of Affect (Russell, 1980).

Martino et al., 2015; Wickramaratne et al., 2022). Social connectedness is a broad term used to reflect the degree to which people feel socially connected within their communities, including within their social networks and social support, together with the general absence of perceived social isolation (Duncan et al., 2021; Wickramaratne et al., 2022). Other terms have been used to reflect the sense of connectedness a person feels, with social networks and support commonly applied. Social networks are defined as the configuration of relationships, including their interconnections, and social support is a product of social relationships that generally refers to care that is provided or immediately available when needed (Haslam et al., 2015). Importantly though, being socially connected is about more than the number of social ties one has or the frequency of interactions. Instead, it reflects the quality and meaningfulness of those connections and can be conceptualized as “the perceived experience of meaningful social connection with others” (Taylor-Jackson et al., 2021, p.285). As Taylor-Jackson et al. (2021, p.285) note, “it is this kind of social engagement that has been consistently associated with positive psychological outcomes”. Social connections have a substantial positive effect on mood and our psychological health and wellbeing (Diendorfer et al., 2021). Following Haslam et al. (2015, p.1), we define social connectedness as “the sense of belonging and subjective psychological bond that people feel in relation to individuals and groups of others”, whilst mood-related social connectedness refers to the influence that social connectedness has on mood (Martino et al., 2015). Social connectedness protects mental health in reducing the likelihood of developing symptoms of depression (Lamblin et al., 2017; McMahon et al., 2022; Wickramaratne et al., 2022). As such, feelings of social disconnection and loneliness both contribute to adverse mental health conditions, including anxiety, depression and mood disorders (Wickramaratne et al., 2022).

2.1.3. Loneliness and social disconnection

Loneliness and social disconnection (SD) are the inverse of social connectedness and have been identified as major health risks around the globe (Diendorfer et al., 2021). For example, one in four Australian and three in five American adults are lonely (Australian Psychological Society, 2018; Cigna, 2020). In the United States loneliness is estimated to cost the economy \$6.7 billion USD annually (Flowers et al., 2017), whilst in Australia it is \$2.7 billion AUD (Duncan et al., 2021). Loneliness is described as unwanted social isolation that is subjective and reflects divergence between a person’s desired social relationships and those they actually have (Haslam et al., 2019). It is typically assessed by capturing a person’s subjective sense of the quality of their social interactions and connections (Green et al., 2018). In contrast, social disconnection is objective and reflects a “long-standing lack of social/family relationships and minimal participation in social activities” (Green et al., 2018, p.1). Reflecting the difference between these two constructs, it is not uncommon for people to feel a sense of loneliness even when surrounded by friends and family and hence be objectively socially connected but subjectively lonely (Green et al., 2018). Loneliness and SD are predictors of all-cause mortality. Both are associated with a range of chronic diseases, including coronary heart disease and stroke; loneliness is also a major risk factor for mental health conditions, including depression and social anxiety, whilst SD is linked to high blood pressure, inflammatory response, and poor immune function (Green et al., 2018; Haslam et al., 2019; Lim et al., 2016; Valtorta et al., 2016). Furthermore, people who are lonely or socially disconnected typically exhibit greater inflammatory responses to psychological stress (Moieni et al., 2015).

2.2. Physiological sensing of mood

The physiological measures that are typically used within mood detection include heart rate (HR), electrodermal activity (EDA) and skin temperature (ST) (Bautista-Salinas et al., 2019; Can et al., 2019; Cecchi et al., 2020; Climent-Pérez et al., 2020; Topoglu et al., 2019). These parameters are frequently used to measure physiological activation of

the Autonomic Nervous System (ANS), which is a key component in mood response, including positive and negative emotions, and includes both the Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS) (Kop et al., 2011; Kreibig, 2010). For instance, HR is one of the most widely used signals for measuring autonomic activation that represents the influence of both SNS and PNS (see (Can et al., 2019; Kanjo et al., 2019; Kop et al., 2011) for more detail), and one which has been used to measure stress and anxiety in ambulatory studies (Trull and Ebner-Priemer, 2013). ST and EDA are also important signals that are often used to measure emotion (see Cecchi et al., 2020; Climent-Pérez et al., 2020; Goshvarpour et al., 2017; Kanjo et al., 2019 for more detail), as they are both linked to emotional arousal and excitement (Can et al., 2019; Cecchi et al., 2020). When utilizing EDA, the raw signal must first be processed to extract two components – Skin Conductance Level (SCL), a slow-moving tonic component, and Skin Conductance Response (SCR), a faster phasic response that is event driven (Can et al., 2019).

In previous work by van der Mee et al. (2021) both tonic (SCL) and phasic (SCR) responses from EDA were measured when participants were exposed to stressors. These researchers reported that subjective stress increased in both positive and negative affect and were associated with higher SCL and increased frequency of SCR. In other work, Loveys et al. (2021) measured heart rate, skin temperature, and EDA when participants were exposed to various emotional expressions from a digital human. Results demonstrated that EDA was significantly higher for men while interacting with an emotional voice, as opposed to a neutral voice, whilst women experienced lower loneliness and subjective stress when they interacted with a neutral face rather than no face. Similarly, Kanjo et al. (2018) measured HR, EDA, ST, motion (via accelerometers), air pressure and light from a wearable wristband, with smartphone-captured noise, location (via GPS) and self-reported emotion whilst participants walked around a city centre. The data revealed a correlation between noise and HR, as well as between light/noise and EDA. Air pressure was also linked to ST and motion and was significantly correlated with HR. Moreover, machine learning results for emotion recognition using Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbor (kNN) and Naïve Bayes (NB) within a stacked model demonstrated an accuracy of 86 % and F1 Score of 84 %. Similarly, Bautista-Salinas et al. (2019) measured the mood of elderly people in everyday life using the Empatica E4 device. Results from four participants using a hold-out method with an SVM classifier achieved accuracies between 70 % - 80 % for the prediction of mood.

2.3. Detection of social connection and loneliness using technology

Previous research on technology and social connection has mainly been undertaken using smartphone data to evidence its effects on college experience, academic performance and depression (Nepal et al., 2024; Wang et al., 2014), and to reduce loneliness (Janssen et al., 2014) through interventions such as instant messaging on smartphones (Jarvis et al., 2019) and videoconferencing (Tsai et al., 2010). A study by Doryab et al. (2019) utilized smartphone data (Bluetooth, calls, SMS, Wi-Fi, location, phone usage), and data from a wearable device (Fitbit Flex 2; steps, sleep status) to infer loneliness and related behavioural patterns in university students. Results from an ensemble machine learning classification model demonstrated a maximum accuracy of 80.2 % for the binary detection of loneliness. Similarly, Nepal et al. (2024), tracked 200 college students over four years using their smartphones to collect data on physical activity, location, phone usage, audio and sleep. Weekly self-reports were also included to assess stress, social level, and COVID concerns via single-item measures, and anxiety/depressions via the Patient Health Questionnaire-4 (PHQ4). The results indicated that the first semester of college was the most critical time for students to adapt to their new learning environment, and establish social connections (Nepal et al., 2024). In Benson et al.’s (Benson et al., 2021) related work, the associations between loneliness and social isolation with sleep quality were explored, whilst participants wore an actigraph device on

their wrist. The findings showed that loneliness and social isolation were associated with disrupted sleep. Additionally, those who felt more lonely reported greater symptoms of insomnia and those who were more isolated spent a longer time in bed (Benson et al., 2021).

In other work, Wu et al. (2021) predicted loneliness using features extracted from smartphone data to construct three models that used Bluetooth only, GPS only or Bluetooth+GPS (geosocial) features. A maximum AUC of 74 % was achieved using the combined Bluetooth+GPS features. Similarly, Sanchez et al. (2015) analysed smartphone data to develop predictive models of loneliness in the context of family and spousal relationships, and periods of social and existential crisis in older adults. This then fed into the development of an Android mobile application that monitored participants' activities and measured perceptions of loneliness in each context. Results achieved accuracies of 91.67 % (family), 83.34 % (spousal), 66.67 % (social) and 83.34 % (existential crisis) in these different contexts.

Previous work that has employed wearable devices have utilised sociometric badges, which are typically identification badges worn by employees of an organisation that are augmented to include sensors to detect communication, proximity, and speaking patterns, to identify social interaction (Gedik et al., 2023; Olguín Olguín, 2011; Zhang et al., 2018). For instance, Zhang et al. (2018) utilised such badges within a small team to detect social interaction patterns. Data from the badges included time of day, which provided temporal context, and the identifiers of other badges to infer who people interacted with. Using latent Dirichlet allocation (LDA), results demonstrated that low dimensional latent structures of interactions can provide insights into social interaction patterns. Similarly, Gedik et al. (2023) utilised sociometric badges to determine the quality of social interactions in a small team during a 4-month simulated space mission. Data from the badges included movement, audio, infrared detection of other badges and Bluetooth. Self-report data was also collected twice daily from participants that included rating satisfaction with their last interaction with other team members, affective state and insights into team cohesiveness. Using Temporal Convolutional Networks (TCN), results demonstrated an average Receiver Operating Characteristics-Area Under Curve (ROC-AUC) of 0.64. Nevertheless, there are limitations in the use of wearable badges in that such badges are often used in organisational contexts whereby employees often wear identification badges (Zhang et al., 2018), which limits generalisability to other contexts outside of a workplace setting. Additionally, the data is restricted to behavioural signals, such as speech, movement and proximity, and does not include physiological signals, which are important to model mood and social connectedness. Furthermore, proximity alone may be misinterpreted as people are near each other but may not be interacting. While these sensing modalities are complementary, further context is required using physiological data to capture physiological links of mood, loneliness and SD. Additionally, this work is situated in extreme and highly structured environments with constrained social groups and task demands, which enables strong assumptions about interaction opportunities and baseline behaviour. In contrast, our study targets every day, naturalistic settings, where social encounters are less predictable and social connectedness is more subjective and internally experienced rather than directly observable through proximity alone.

A major limitation in our understanding of loneliness is the lack of high-quality real-world data — in particular data relating to people's time- and location-based lived experience of loneliness, its triggers, correlates with physiological activation, and outcomes. The physiological correlates of loneliness and SD are an especially rich source of data, which can be obtained from wearable devices to provide an objective index of where and when these feelings are experienced (not just in laboratories). For instance, physiological activation measures of the ANS that are related to mood, including valence and activation, are also important for social connectivity, as positive valence and high activation can combine with positive social connections to activate the ANS (Bosle et al., 2022; Kusserow et al., 2013). However, loneliness can

overstimulate the SNS, leading to suppression of the PNS, which can have harmful effects on health (Li and Xia, 2020). Furthermore, social disconnection has been shown to also influence cardiovascular measures and affective reactivity (Williamson et al., 2018). Technological advancement therefore has the potential not only to capture activation of the ANS, but also to influence the health of individuals and communities in general — not least by raising awareness of the experience and consequences of SD through the continuous, automatic, and unobtrusive collection of psychophysiological data. The increasing affordability and pervasiveness of wearable devices also facilitates the collection of just such objective measures and represents a source of data that avoids the biases that are inherent in self-reported, or laboratory-captured data (Arae et al., 2016).

In summary, whilst a large body of existing literature focuses on the detection of mood, very little work has been undertaken in coupling detection of mood with detecting loneliness and social disconnection using physiological data from wearable devices. The methodology of the present study included extracting a number of physiological features from a wearable device that are representative of ANS activation for the parameters that were being measured — namely mood and social connection (Can et al., 2019; Cecchi et al., 2020; Ghiasi et al., 2020). The contribution of the present work provides a framework for detecting mood, general social connectedness, and in-the-moment social connection in everyday life using a lifelogging data collection platform and supervised machine learning.

3. Materials and methods

3.1. Participants

The sample comprised 50 university students (23 females and 27 males), whose age ranged between 18 and 54 years (mean = 26.46, SD = 6.3). Participants had no history of cardiovascular illness (e.g., heart disease, arrhythmia) and were not pregnant at the time of the study. Prior to the study, all procedures for participant recruitment and data collection were approved by the Human Ethics Committee at the first author's university.

3.2. Data collection platform and procedure

The mobile lifelogging system utilized commercially available devices to collect data across two consecutive weekdays as participants went about their daily lives. An average of eight hours of data were collected each day, with data collection starting around 9am until 5pm. In total, 746 h of raw data was collected.

The platform used to collect data included an Empatica™ E4 Wristband and Samsung™ Galaxy J5 Pro Smartphone, which were supplied to every participant. The E4 wristband used a variety of sensors to capture several streams of raw physiological data, at various fixed sampling rates. The physiological sensors and measures included:

- Photoplethysmography (PPG) sensor to measure Blood Volume Pulse (BVP) at 64 Hz, used to derive Inter-Beat-Interval (IBI) and Heart Rate (HR) using E4's proprietary algorithms. HR has been calculated at a sampling rate of 1 Hz.
- Electrodermal Activity (EDA) to measure raw skin conductance at a sampling rate of 4 Hz.
- Infrared Thermopile sensor to measure exterior Skin Temperature (ST) at a sampling rate of 4 Hz.
- 3-axis (X, Y, Z) accelerometer (ACC) to measure motion at a sampling rate of 32 Hz.

Note that Heart Rate Variability (HRV) was not calculated as this measure is significantly impacted by movement, which compromises the accuracy of the measurement (Stuyck et al., 2022). As this study was undertaken in the wild as participants were going about their daily lives,

movement could not be constrained. A custom-developed Android application was also created for the study as a method for administering a self-report questionnaire, which participants were required to complete every two hours (see Section 3.3 for details of the self-report questionnaire). Upon starting the study, participants received a demonstration of the equipment before completing the first self-report questionnaire, which required them to rate their social connectedness and mood. Participants were then free to engage in their normal daily routine. The only requirement was that they had to wear the wristband and complete the self-report questionnaire every two hours at 10am, 12pm, 2pm and 4pm. After data collection was completed, participants returned the equipment and were debriefed and given a \$50 AUD gift voucher to thank them for their participation.

3.3. Experimental measures

Using a custom-developed Android application, participants were required to answer a brief version of the UWIST Mood Adjective Checklist (UMACL) (Matthews et al., 1990); as well as two questions about social connectivity and a third question requiring them to estimate the number of people around them. The rationale for utilising the UMACL is because it is a validated self-report questionnaire that is based on the Russell's (1980) Circumplex Model of Affect (Matthews et al., 1990), which, as defined in Section 2, is the theoretical model of mood that underpins this paper. UMACL has identified significant correlations between arousal/valence and psychophysiological measures of automatic arousal (Matthews et al., 1990), which makes it a suitable measure for this paper in linking subjective mood with objective physiological data. This is not the case with other scales, including emoji scales that fails to measure all the required dimensions and can be susceptible to bias due to the difficulty of reporting in-the-moment mood (Kaye and Schweiger, 2023).

The UMACL questionnaire comprises three bipolar subscales of Energetic Arousal (EA), Tense Arousal (TA) and Hedonic Tone (HT), which mediates mood, and a unipolar dimension of Anger (Boyle et al., 2015; Matthews et al., 1990). EA is associated with positive affect and activation related to alertness (awake/energetic – tired), with higher EA levels relating to more pleasurable mood (Witowska and Zajenkowski, 2019). HT is related to valence (pleasant – unpleasant), with negative (low) HT being related to anxiety, sadness, and depression, whilst TA measures tension vs. calmness (Boyle et al., 2015; De Dreu et al., 2008). EA and HT were selected as they capture the two fundamental dimensions of mood on which this paper is based (arousal and valence) (De Dreu et al., 2008).

The questionnaire contained 14 adjectives of feelings that participants self-rated to indicate how they felt in relation to that word in that moment (e.g., calm, alert, tense) using a 4-point Likert Scale (1 = *strongly disagree*, 4 = *strongly agree*). Each of the bipolar subscales consisted of four adjectives, in which two adjectives were positively worded and two were negatively worded. For each subscale, the two negative items were reverse scored. Following Eq. (1), each subscale (s_c) was calculated by summing the two positive items (pos) and subtracting the sum of the negative items (neg) to derive a single score.

$$s_c = (pos^1 + pos^2) - (neg^1 + neg^2) \quad (1)$$

To assess feelings of social connectivity we focused on several key elements reported in previous intensive longitudinal research on social interactions using experience sampling methodology; notably, the presence of others around a respondent (i.e., who they are with), and their sense of closeness and emotional connection in general (i.e., the quality of connectedness to others in one's general community) and to those around them (i.e., the quality of the interaction to specific people) in the moment (i.e. (Prochnow et al., 2025; Stadel et al., 2024)). Specific questions were as follows:

- Q1: General feelings of social connection: *How connected do you feel to other people in general right now?*
- Q2: Social density and presence of others in the vicinity: *Right now, how many people are currently within a 5 m radius of you?* [numeric open-ended response]
- Q3: Feelings of social connection to people in the vicinity: *Assuming there are some people nearby, how connected do you feel to those people right now?*

The social connectivity questions 1 and 3 were scored on a 4-point Likert Scale (1 = not at all connected, 4 = very connected). There were also additional options for 'prefer not to say' and 'N/A' (in the case of question 3 only). The purpose of these questions was to measure different aspects of *state* social connection. The first question (feeling connected to people) was intended to index a general feeling of social connectedness in the moment and thus was unrelated to physical proximity to other people, whereas the third question captured in-the-moment social connection in association with proximity. This separation of general social connection (Q1) from social connection to those in one's physical proximity (Q3), was intended to capture the breadth of experience in social connection. This manifests in many ways — going beyond one's sense of connection to the individuals, friends or family members you might be in contact with, to also include a wider sense of connection and belonging to a larger community (Vella et al., 2019).

3.4. Data processing pipeline

Responses to the questions and the raw physiological data from the E4 wristband (HR, EDA, ST, and ACC) were processed for each participant, per data collection day. Data pre-processing was performed using MATLAB vR2020a. Fig. 2 illustrates the design of the data processing pipeline that was developed. The initial dataset was composed of 121,020,958 instances of raw data.

In the first instance, the EDA, ST, and ACC signals were downsampled to 1 Hz. It was necessary to downsample the signals, particularly the ACC, to align the data resolution with other physiological signals, such as HR, in order to focus on broader patterns of behaviour. This is common practice in the literature (Gjoreski et al., 2016). As the purpose of the paper was not to analyse high-density motion or micro-movements, 1 Hz was suitable to capture the required information (Gjoreski et al., 2016). An initial check was first performed to determine any periods where the wristband may have lost contact with the skin. This check was undertaken using the temperature data stream to ascertain if the temperature was out of range of normal human body temperature. This data stream was chosen on the basis of literature recommendations (Kleckner et al., 2018) and pilot testing, which included observing the signals when the wristband was not being worn. If the temperature was either $< 30^\circ\text{C}$ or $> 40^\circ\text{C}$ this was deemed to indicate loss of contact with the skin (Kleckner et al., 2018) and the corresponding data were marked as invalid across all data streams. This resulted in 1.78 % of the data being discarded.

Filtering and measures were extracted from the ACC and EDA signals, as HR had already been processed by the E4 algorithms and filtering wasn't required for the ST data stream. The raw EDA data stream was processed using the cvxEDA (Greco et al., 2016) algorithm to extract the phasic skin conductance response (SCR) and tonic skin conductance level (SCL) components of the signal. This algorithm uses Bayesian statistics, mathematical convex optimization, and sparsity to decompose the signal, and thus does not require filtering (Greco et al., 2016). The individual accelerometer signals of the x, y, and z axis were processed to first remove the DC component of the signal by subtracting the mean of each signal from the signal. A 2nd order lowpass Butterworth filter, with a cutoff frequency of 0.5 Hz, was then applied to the signals. They were then combined into one vector to represent overall acceleration vector magnitude (ACC_VM) by squaring each axis and

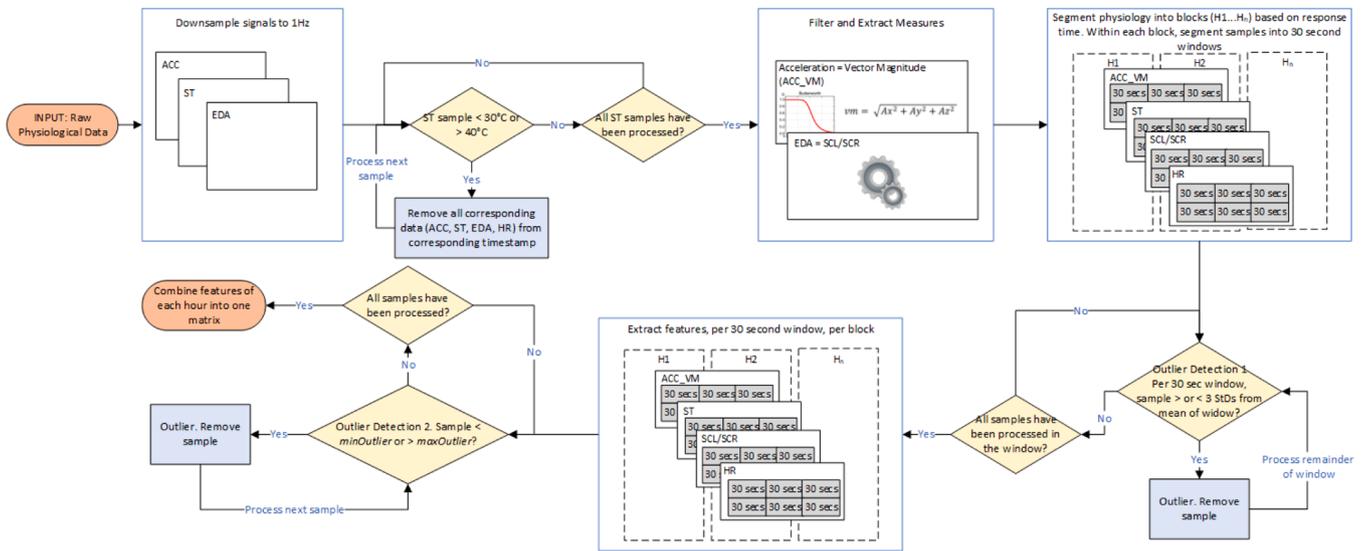


Fig. 2. Design of the data processing pipeline.

summing them together before taking the square root ($\sqrt{x^2 + y^2 + z^2}$) (Servia-Rodríguez et al., 2017).

The response time to the subjective questionnaires were used as an anchor to analyse the physiology. The raw sensor data were segmented into blocks, based on the response time to the questions (i.e., the first block (H1) consisted of data from the start of the experiment up until the first questionnaire at 10am, H2 was segmented between 10am – 12pm, and so on). For each block, each physiological data stream was individually processed in 30-second windows.

The approach to identify outliers was then undertaken in two stages. First, the 68–95–99.7 rule (Empirical Rule) was used to remove outliers within each 30-second window of data. This is a standard rule in statistics that denotes that 99.7% of observations are typically within three standard deviations of the mean (Dunn, 2021). Thus, any samples that were greater than or less than three standard deviations away from the mean of the window were considered an outlier and marked as invalid. For each data stream (HR, SCL, SCR, TEMP, ACC) a set of eight statistical features were extracted from each cleaned 30 s window of data, including mean, median, standard deviation, minimum, maximum, variance, 25th percentile and 75th percentile. This resulted in a matrix of 40 features (i.e., 8 statistical features x 5 measures [HR, SCR, SCL, TEMP and ACC]) x 96,277 rows (i.e., ≈ 1925 rows per participant x 50 participants) = 3851,080 features. These features were based on the literature (Campanella et al., 2023; Chandra et al., 2021; Shu et al., 2018) and were selected due to their ability to capture essential characteristics of the data, including central tendency (mean, median), dispersion (standard deviation, variance), extremes (minimum, maximum) and distribution (25th and 75th percentiles), while maintaining simplicity and interpretability.

Once all of the data streams had been processed and features extracted, a final outlier check was then performed on each time block of extracted features to ensure that the features did not contain any additional outliers. This was undertaken using a modified version of Tukey's Boxplot (Schwertman et al., 2004), which is a common and simple outlier detection method using interquartile range (Schwertman et al., 2004). For each feature column per time block, the 25th ($q1$) and 75th percentile ($q3$) were calculated, as well as the interquartile range (iqr). Outliers were identified using Eqs. (2) and (3) to determine the minimum ($minOutlier$) and maximum ($maxOutlier$) outlier limits. If a sample (s) was less than the 25th percentile ($q1$) minus 1.5 times the iqr it was identified as a $minOutlier$ and marked as invalid. If a sample (s) was more than the 75th percentile ($q3$) plus 1.5 times the iqr it was identified as a $maxOutlier$ and marked as invalid.

$$minOutlier = s < (q1 - (1.5 \times iqr)) \quad (2)$$

$$maxOutlier = s > (q3 + (1.5 \times iqr)) \quad (3)$$

The outlier detection approach was designed to be comprehensive to detect outliers both in relation to the raw data and also within the extracted features. Once all the time blocks were processed, they were then combined into one matrix, per participant. The data were then normalized by calculating the Z-score for each feature, per participant per day. This was undertaken to account for individual differences between the participants. The datasheets were then combined into one master sheet that included all days and participant data.

3.5. Data labelling

Before the classification analysis could be undertaken, the data were labelled using the subjective reports. In line with the literature (Mäder et al., 2024; Meegahapola et al., 2020; Servia-Rodríguez et al., 2017), the dataset for analysis was reduced to include only the features (i.e., per 30-second epochs) that occurred within 10-minutes before and after participants responded to the questions (i.e., 20 min total). The purpose of this was to synchronize the physiological data around the time of in-situ subjective self-reports (Mäder et al., 2024). This ensured that the labels that were generated to distinguish change in subjective mood and social connection were situated around the time that the self-reports were submitted. This was necessary because the self-reports captured mood and social connection at specific intervals, as participants rated how they felt at the time. This, then, was a deliberate decision to tap into momentary emotional episodes as a 'snapshot' in time (Boyle et al., 2015). Note that generalising the self-report outcomes and physiology over each 2-hour block would not provide an accurate reflection of their affective states over this entire period of time, as mood states and social connectivity are transient (Boyle et al., 2015).

The dimensions of the final dataset for analysis included 40 features x 17,026 rows (i.e., ≈ 340 rows per participant x 50 participants) = 681,040 features. Using this dataset, the analysis included constructing five binary models that were classified as higher or lower in mood/connectedness for EA, HT and the three social connection questions (Q1 – Q3). Binary models were chosen to detect and examine the extreme cases that were associated with the high and low end of the spectrum. All Likert responses for the social connection questions that were equal to 5 (Prefer not to Say) or 6 (N/A) were removed prior to labelling. To generate the labels, we calculated the mean for each measure of EA, HT,

and the social connection items (per day, per participant; (Zhang et al., 2020)). The data were labelled as follows:

- Greater than the mean was labelled as “high”
- Less than the mean was labelled as “low”

In this way, the labelling process was *personalized* to each participant and to the day that data were collected. Data equal to the mean were excluded (Zhang et al., 2020). The rationale for the exclusion of data points was that those equal to the mean were neither above nor below and hence they introduce ambiguity into the model. To maintain a clear binary distinction, these points were excluded as they were neutral points that did not fit clearly into either category of *high* or *low*. Indeed, as our primary purpose was to examine the extremes of high vs. low, neutral points would introduce noise and be detrimental to our analysis. Fig. 3 illustrates the distribution of input data and the proportion of excluded data per model.

As it can be seen in Fig. 3, the labelling process resulted in the exclusion of a small amount of data. Question three resulted in a larger amount of data being excluded because of the additional ‘N/A’ option for this question as the question assumed that there were people nearby.

3.6. Classification model design

The classification analysis utilized a suite of parametric and non-parametric classifiers, including *k*-Nearest Neighbors (kNN), Support Vector Machines (SVM), Random Forest (RF) and Naïve Bayes (NB), to determine the best approach for distinguishing between higher and lower mood and social connectedness. These are some of the most widely used algorithms in the area (Can et al., 2020; Das et al., 2016; Shu et al., 2018). For instance, SVM is the most widely utilised algorithm in physiological signal-based emotion recognition but its ability to classify unbalanced datasets is limited (Das et al., 2016; Shu et al., 2018). kNN is the most straightforward algorithm to implement as it classifies data using the nearest neighbour method and works best when there is a clear separation in labels. However, a drawback is that all of the training sets

are stored, which increases complexity (Das et al., 2016; Shu et al., 2018). RF is a tree-based ensemble algorithm that learns by sub-setting the feature set (Gjoreski et al., 2017). NB has lower computational demand than the other algorithms. It is based on probabilistic formulation and so regards features as independent (Das et al., 2016). Each classifier was analysed independently for each model. Fig. 4 illustrates the design of the binary classification model pipeline that was replicated per model.

Each model was created using the *mlr3pipelines* dataflow programming toolkit (Becker et al., 2021) to construct a PipeOp-object (PO). POs are machine learning workflows that represent the data flow from pre-processing to model fitting (Becker et al., 2021). The pre-processing steps in this pipeline involved first imputing any remaining missing data via the *PipeOpImputeHist* PO, using numeric values that were calculated from a histogram per feature column. This is an established method for dealing with missing data (Xindong Wu et al., 2014). The classes were then automatically balanced through implementation of the *PipeOp-ClassBalancing* PO, which upsampled the minority class until the ratio equalled the maximum count of the majority class for each analysis. The upsampled data were then shuffled amongst the original data. Balancing the classes was another essential step in the pipeline as unbalanced data produces biased models (Chawla et al., 2003).

Using the *PipeOpFilter* PO, automatic feature selection was then performed using Information Gain (IG) to reduce the feature set. This method is commonly used within machine learning analysis as a “term-goodness criterion” that is based on entropy (Alhaj et al., 2016). Each feature’s information gain was calculated independently to measure its importance and relevance to the class labels (Alhaj et al., 2016). The pipeline was then encapsulated as a learner before being passed into an AutoTuner class so that the parameters of each model could be tuned.

Each model utilized a nested cross-validation approach, which resulted in an inner and outer resampling loop (see Fig. 4), whereby the same data was not used in both the training and testing sets. This method was chosen as opposed to leave-one-out-cross-validation (LOO—CV) due to nested cross-validation having lower variance and the ability to achieve an unbiased estimation of performance by preventing data leakage, which could result in overfitting, through the incorporation of

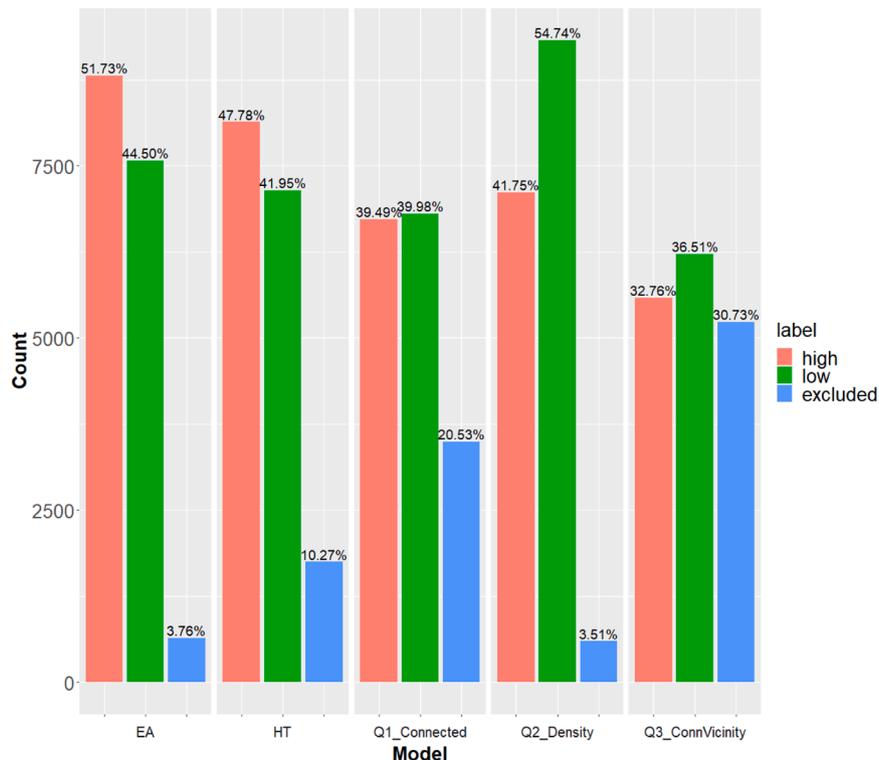


Fig. 3. Distribution of labels per model. Note: percentages indicate proportion of each label.

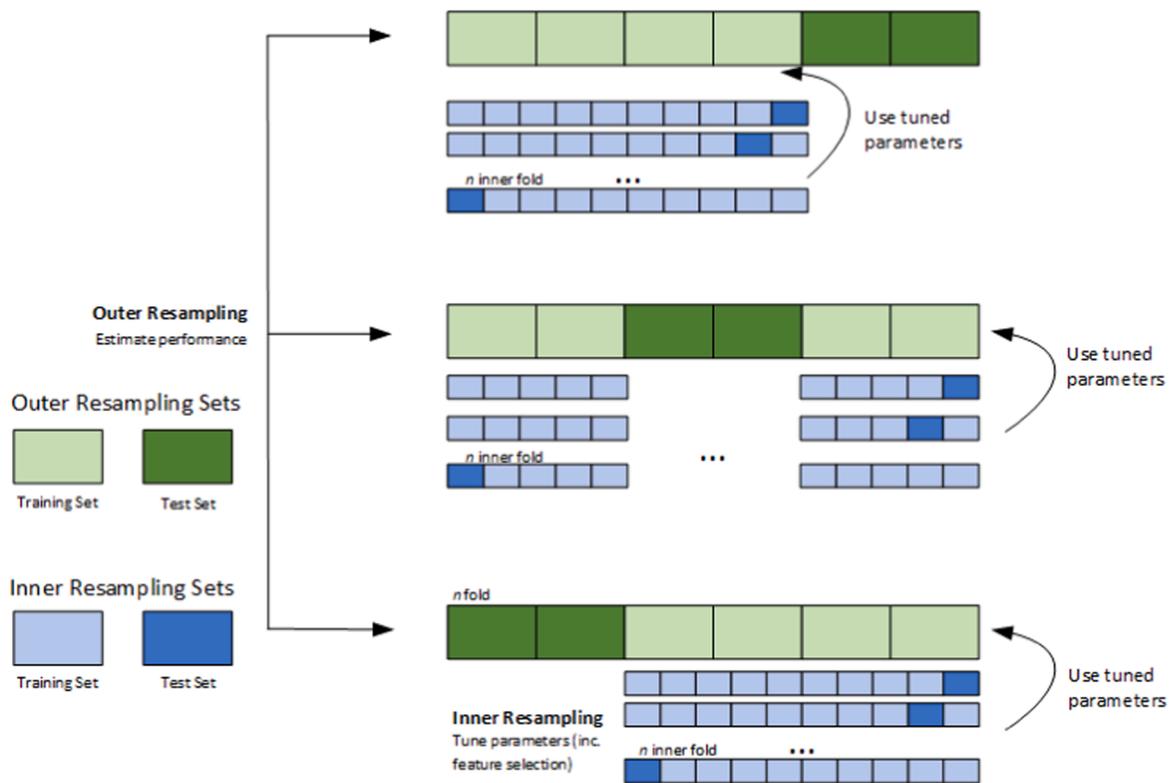


Fig. 4. Design of the classification model pipeline. Nested cross-validation approach adapted from (Becker et al., 2021).

an inner validation loop for hyperparameter tuning (Becker et al., 2021; Bischl et al., 2012; Douglas et al., 2011). In this way, this approach of nested cross-validation produces unbiased results by separating the feature selection/hyperparameter tuning from the performance estimation of the model (Becker et al., 2021). Fig. 4 illustrates the approach used in this paper, which utilized k -fold cross-validation, in which $k = 10$ in the inner resampling loop and $k = 5$ in the outer resampling loop. Each model was evaluated using only the outer test set to prevent data leakage (Bischl et al., 2012). For each outer training set, the inner resampling loop was triggered to select the best set of hyperparameters for that particular outer training set (fold). This included performing the pre-processing steps detailed above and hyperparameter tuning. The inner loop performed its own k -fold cross-validation ($k = 10$) to select the best set of hyperparameters. The inner loop tuned the hyperparameters on $k - 1$ of the inner folds (i.e. 9 folds) and validated on the remaining fold. This was repeated until all of the inner folds were validated. The Random Search tuning algorithm (Bergstra and Bengio, 2012) was used and this entire inner k -fold cross-validation process was repeated five times to select the configuration that produced the best performance across all the inner folds. The outer loop then used the selected hyperparameters in the outer training set. In this way, each outer training set had its own set of tuned parameters, whilst performance was calculated using the outer test set (Becker et al., 2021; Bischl et al., 2012). Most importantly, the inner loop's only purpose was to select hyperparameters that generalised well within the outer training set and so it never utilised the outer test data. Similarly, the outer test set was never used for tuning. Although this method is computationally very expensive, it is a robust method to ensure unbiased results (Bischl et al., 2012).

Although feature selection was performed during all analyses, tuning was not performed for NB as it is a simplistic model with very few hyperparameters. However, as feature selection was performed for NB, the nested cross-validation approach was still undertaken. The hyperparameters that were tuned for the other models included: kNN: k and distance

- SVM: cost, gamma, kernel, and degree
- RF: number of threads and number of trees.

The tuned hyperparameters for all of the outer folds of each model can be found in Appendix 1 – 4, along with the classification error of each fold, as each outer fold produces its own classification error based on its test set.

4. Results

Our data analysis first examined the subjective questionnaire responses to ascertain participants' subjective feelings of mood and social connectivity. The physiological features were then used within five binary classification models to detect mood, in terms of (a) Energetic Arousal (EA) and (b) Hedonic Tone (HT), as well as social connectivity, in terms of (c) general feelings of social connectedness (Q1), (d) the presence of other people in the immediate area (Q2), and (e) feelings of social connection to those people (Q3). The analysis was undertaken using R v4.2.0.

4.1. Subjective questionnaire results

The subjective mood and social connectivity data for three participants were excluded from the subjective analysis due to missing questionnaire responses. Additionally, responses for the social connection questions (Q1 and Q3) that were equal to "Prefer not to Say" or "N/A" were removed. The descriptive statistics for the remaining data are illustrated in Fig. 5.

A two-way repeated measures ANOVA was performed for each measure to evaluate the differences between the time points across both days of data collection. There was a statistically significant effect between day and the timepoints on EA, $[F(3.39, 155.79) = 3.6, p = 0.012]$. Post-hoc tests, using Bonferroni correction, revealed significant differences at Hour 2 only ($p = 0.006$). Additional pairwise comparisons, using paired t -test, showed that EA was significantly different between

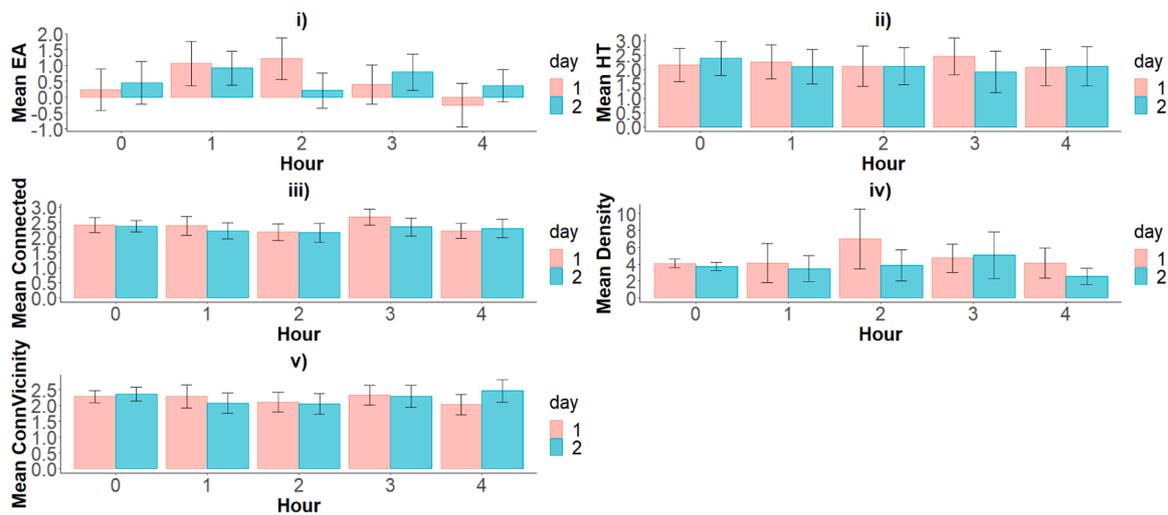


Fig. 5. Mean subjective responses, with 95 % confidence interval, per time point (0 = baseline, 1 = 10am, 2 = 12pm, 3 = 2pm, 4 = 4pm) for i) Energetic Arousal (EA), ii) Hedonic Tone (HT), iii) general social connection (Q1), iv) social density estimation of people within the vicinity (Q2) and v) social connection to those within the immediate vicinity (Q3).

the days at hour 2 only ($p = 0.0171$). The HT analysis [$F(4, 184) = 1.22, p = 0.303$] did not reveal any significant changes across the hours or days. Post-hoc tests, using Bonferroni correction also found no significant differences. General feelings of social connection (Q1) revealed no significant effect between day and the timepoints [$F(4, 184) = 1.08, p = 0.367$]. However, post-hoc tests, using Bonferroni correction, revealed a significant effect of day at Hour 3 only ($p = 0.048$). Additional pairwise comparisons, using paired t -test, found no significant differences between the days. Feelings of social connection to those in the immediate vicinity (Q3) revealed no significant effect between day and the timepoints [$F(4, 124) = 1.35, p = 0.256$]. However, post-hoc tests, using Bonferroni correction, revealed a significant effect of day at Hour 4 only ($p = 0.02$). No additional differences were found with paired t -test comparisons.

An analysis of the relationship between the subjective states was also undertaken. Fig. 6 depicts the resulting correlation matrix for the subjective states gathered via the self-report questionnaire.

As illustrated in Fig. 6, there was a moderate correlation between EA and HT (0.49) and a very low correlation between EA and social density (0.03) and connection to those in the vicinity (0.06), as well a low correlation to general social connection (0.22). HT demonstrated a very low negative correlation with social density (-0.04) and a low correlation with social connection (0.29) and very low correlation to

connection to those in the vicinity (0.07). General social connection had a very low (0.02) correlation with social density and a low (0.29) positive correlation with connection to those in the vicinity, whilst social density had a low negative correlation to connection to those in the vicinity (-0.21). This suggests (a) weak associations between indicators of the subjective states under examination, which in turn suggest the different classification models were likely sufficiently discrete to represent different psychophysiological subjective scales related to different aspects of mood and social connectedness.

4.2. Classification results

The classification evaluation involved constructing five individual binary classification models using the design in Fig. 4. In this instance, the positive class in each model was “high”, whilst the negative class was “low”. The performance metrics used to assess classification comprised:

- Accuracy — overall measure of performance of a classifier’s ability to distinguish between the positive and negative classes.
- F1 Score —harmonic mean of a classifier by combining precision (i. e., Positive Predictive Value (PPV)) and recall (i.e., True Positive Rate (TPR)),
- Sensitivity (True Positive Rate (TPR)/recall) —proportion of correctly classified positive instances.

These performance metrics were chosen as they represent the most commonly used measures in binary classification that capture a holistic view of performance (Sokolova and Lapalme, 2009). The results for each model depict the average classification performance across all five outer folds and include standard deviations for each performance metric in brackets and the best performance in bold. Additionally, in any binary model the theoretical probability of a random classification by chance is 50/50 (i.e., 50 %) and so when evaluating accuracy, the assessment should take into consideration how much the results differ from a purely random result (Combrisson and Jerbi, 2015). However, a 50 % level of chance is assumed for an unlimited number of samples in the dataset and so this level should be adjusted depending on the sample size of the dataset (Combrisson and Jerbi, 2015). In line with Combrisson and Jerbi (2015), a binomial cumulative distribution was calculated to derive statistically significant thresholds for each model. When considering the different sample sizes of each dataset for each model, the adjusted threshold for statistical significance at $p < 0.05$ was 0.51 for all models.

For each classification problem, further tests were performed to

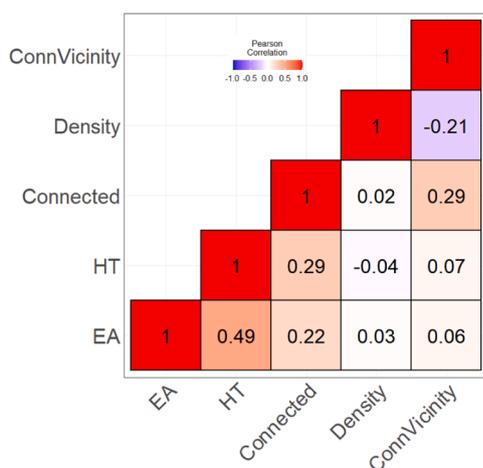


Fig. 6. Pearson correlation matrix between the measures.

assess the statistical significance of the results. These included: (1) comparing each classifier's accuracy with chance to determine if the classifiers were performing above chance using paired *t*-tests and (2) comparing accuracy of the different classifiers for each problem using one-way ANOVA models. For each classification model, *p*-values have been represented as: ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

4.2.1. Classification of mood

The purpose of this classification was to differentiate mood in terms of energetic arousal (EA) and hedonic tone (HT). The EA and HT classification results in Table 1 and Table 2, respectively, indicate that Random Forest outperformed all other classifiers and demonstrates that this classifier was more accurate at correctly detecting energetic arousal and hedonic tone. In relation to the EA model, the tuned hyperparameters in the random forest model that performed the best included 17 features, 5 threads, and 16 trees, which yielded a classification error of 0.16 (see Appendix 1). The results of paired-sample *t*-test for each classifier against chance in the EA model (see Table 1) indicated that the accuracy of all classifiers was significantly above chance. Additionally, the ANOVA of classifier performance indicated that there were significant differences between the classifiers [$F(3, 16) = 63.03, p = 0.00, \eta^2 = 0.92$]. Tukey post-hoc analyses revealed that all classifiers were statistically different to each other.

In relation to the HT model, the tuned hyperparameters in the random forest model that performed the best included 12 features, 14 threads, and 19 trees, which yielded a classification error of 0.17 (see Appendix 1). Results of *t*-tests for each classifier against chance in the HT model (see Table 2) indicated that the accuracy of most of the classifiers was significantly above chance. Additionally, ANOVA of classifier performance indicated that there were significant differences between the classifiers [$F(3, 16) = 21.31, p = 0.00, \eta^2 = 0.80$]. Tukey post-hoc analyses revealed that most classifiers were statistically different to each other, apart from kNN and SVM ($p = 0.0888$) and NB and SVM ($p = 0.2090$).

4.2.2. Classification of general social connection

The purpose of this classification was to detect general feelings of social connection with respect to Q1. The results in Table 3 illustrate that Random Forest outperformed all other classifiers — indicating again that this classifier was better at correctly detecting general feelings of social connection. In relation to the model for Q1, the tuned hyperparameters in the random forest model that performed the best included both 27 features, 8 threads, and 10 trees and 33 features, 7 threads, and 19 trees, which both yielded a classification error of 0.19 (see Appendix 1). Results of paired-sample *t*-test for each classifier against chance in the general social connection model indicated that the accuracy of all classifiers were significantly above chance. Additionally, ANOVAs of classifier performance indicated that there were significant differences between the classifiers [$F(3, 16) = 231.10, p = 0.00, \eta^2 = 0.98$]. Tukey post-hoc analyses revealed that all classifiers were statistically different to each other.

4.2.3. Classification of social density and proximity social connection

Examination of social connection to people within the immediate

vicinity of participants was undertaken in two phases. The first model made a binary distinction of the density of people within a 5 m radius (based on Q2) to depict social density (see Table 4). This was followed by another model that examined in-the-moment self-reported social connection to those people that was based on Q3 (see Table 5). The social density and proximity social connection classification results in Table 4 and Table 5, respectively, indicated that the results were comparable to the previous analysis in that RF again outperformed the other classifiers, against all metrics for both models.

In relation to this model for Q2, the tuned hyperparameters in the random forest model that performed the best included three combinations of 19 features, 9 threads, and 17 trees, 27 features, 19 threads, and 17 trees, and 30 features, 8 threads, and 17 trees, which all yielded a classification error of 0.19 (see Appendix 1). Results of paired-sample *t*-tests in Table 4 for each classifier against chance in the social density estimation model (responses to Q2) indicated that the accuracy of most classifiers was significantly above chance, although SVM was not significant in this case. Additionally, ANOVA of classifier performance indicated that there were significant differences between classifiers [$F(3, 16) = 19.90, p = 0.00, \eta^2 = 0.79$]. Tukey's post-hoc analyses revealed that most classifiers were statistically different to each other, apart from kNN and RF ($p = 0.2280$) and NB and SVM ($p = 0.8830$).

In relation to the model for Q3, the tuned hyperparameters in the random forest model that performed the best included 22 features, 10 threads, and 20 trees, which yielded a classification error of 0.16 (see Appendix 1). Results of paired-sample *t*-tests in Table 5 for each classifier against chance in the social connection within the vicinity model (responses to Q3) indicated that the accuracy of most classifiers was significantly above chance, although again SVM was not significant in this case. Additionally, ANOVA of classifier performance indicated that there were significant differences between the classifiers [$F(3, 16) = 63.64, p = 0.00, \eta^2 = 0.92$]. Tukey's post-hoc analyses revealed that most of the classifiers were statistically different from each other, apart from NB and SVM ($p = 0.9990$).

5. Discussion

The results indicate that wearable sensors capturing physiological data can detect mood and feelings of social connectedness in everyday life. The classification analysis involved constructing five individual models to detect energetic arousal (activation), hedonic tone (valence) and general feelings of social connection before moving on to detecting the sense of social connection that people had with others in their immediate vicinity.

The subjective data analysis (Fig. 5) revealed that participants' mood had a diurnal effect such that it rose in morning and decreased in the afternoon. This is in line with evidence reported in the extant research literature, as EA influences motivation and is often found to be the highest mid to late morning (Thayer, 2012). Additionally, the increased social connection and HT observed at timepoints 3 and 4 could be linked to socializing, as these timepoints generally coincided with 2PM and 4PM. These findings are also in line with previous work, which has found that mood tends to peak at around 1PM (Ogden et al., 2022). The results in Fig. 6 also indicated that the metrics used for labelling the data were uncorrelated, suggesting that the different machine learning

Table 1
Mean classification performance and paired T-Tests, T (4), results of the EA models.

Model	Average Classification Performance			Paired-Sample T-Test			
	Accuracy	F1 Score	Sensitivity	Difference in means	95 % CI	t	p
kNN	0.70 [0.04]	0.71 [0.04]	0.70 [0.04]	-0.19	[-0.24, -0.14]	-10.09	0.0005***
RF	0.82 [0.01]	0.84 [0.01]	0.85 [0.01]	-0.32	[-0.33, -0.30]	-55.85	0.0000****
SVM	0.61 [0.05]	0.67 [0.05]	0.72 [0.13]	-0.11	[-0.17, -0.04]	-4.35	0.0122*
NB	0.53 [0.01]	0.59 [0.04]	0.64 [0.11]	-0.02	[-0.03, -0.01]	-7.66	0.0016**

Note: bold denotes best performance for each classification metric. ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

Table 2

Mean classification performance and paired T-Tests, T (4), results of the HT models.

Model	Average Classification Performance			Paired-Sample T-Test			
	Accuracy	F1 Score	Sensitivity	Difference in means	95 % CI	t	p
kNN	0.70 [0.05]	0.71 [0.05]	0.70 [0.07]	-0.19	[-0.26, -0.12]	-7.65	0.0016**
RF	0.80 [0.04]	0.81 [0.03]	0.81 [0.04]	-0.29	[-0.34, -0.25]	-18.01	0.0001****
SVM	0.60 [0.09]	0.60 [0.21]	0.66 [0.34]	-0.1	[-0.21, 0.02]	-2.4	0.0741 ns
NB	0.53 [0.01]	0.58 [0.01]	0.62 [0.04]	-0.02	[-0.04, -0.01]	-4.54	0.0105*

Note: bold denotes best performance for each classification metric. ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.**Table 3**

Mean classification performance and paired T-Tests, T (4), results of the general social connection (Q1) models.

Model	Average Classification Performance			Paired-Sample T-Test			
	Accuracy	F1 Score	Sensitivity	Difference in means	95 % CI	t	p
kNN	0.76 (0.02)	0.75 (0.01)	0.74 (0.01)	-0.25	[-0.27, -0.23]	-36.9	0.0000****
RF	0.81 (0.004)	0.80 (0.005)	0.79 (0.01)	-0.3	[-0.30, -0.29]	-148.89	0.0000****
SVM	0.58 (0.03)	0.54 (0.08)	0.50 (0.12)	-0.08	[-0.11, -0.04]	-5.46	0.0055**
NB	0.55 (0.01)	0.53 (0.03)	0.51 (0.06)	-0.04	[-0.06, -0.03]	-7.46	0.0017**

Note: bold denotes best performance for each classification metric. ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.**Table 4**

Mean classification performance and paired T-Tests, T (4), results of the social density (Q2) models.

Model	Average Classification Performance			Paired-Sample T-Test			
	Accuracy	F1 Score	Sensitivity	Difference in means	95 % CI	t	p
kNN	0.73 [0.05]	0.70 [0.05]	0.72 [0.05]	-0.23	[-0.28, -0.17]	-10.52	0.0005***
RF	0.81 [0.02]	0.78 [0.02]	0.77 [0.03]	-0.3	[-0.32, -0.28]	-38.08	0.0000****
SVM	0.58 [0.11]	0.52 [0.17]	0.58 [0.30]	-0.08	[-0.21, 0.06]	-1.57	0.1916 ns
NB	0.56 [0.01]	0.1 [0.04]	0.06 [0.03]	-0.05	[-0.06, -0.04]	-9.94	0.0006***

Note: bold denotes best performance for each classification metric. ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.**Table 5**

Mean classification performance and paired T-Tests, T (4), results of the proximity social connection (Q3) models.

Model	Average Classification Performance			Paired-Sample T-Test			
	Accuracy	F1 Score	Sensitivity	Difference in means	95 % CI	t	p
kNN	0.76 [0.02]	0.75 [0.02]	0.76 [0.02]	-0.25	[-0.28, -0.23]	-26.88	0.0000****
RF	0.84 [0.01]	0.82 [0.01]	0.82 [0.01]	-0.33	[-0.34, -0.33]	-133.81	0.0000****
SVM	0.58 [0.07]	0.48 [0.26]	0.55 [0.36]	-0.07	[-0.16, 0.02]	-2.2	0.0922 ns
NB	0.58 [0.01]	0.46 [0.03]	0.40 [0.04]	-0.07	[-0.08, -0.05]	-10.57	0.0005***

Note: bold denotes best performance for each classification metric. ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

models were distinct from one another.

The classification models were implemented according to the design depicted in Fig. 4, which took a binary approach. The machine learning pipeline that was created ensured that an unbiased estimation of performance was obtained by separating the pre-processing and feature selection/tuning from the performance estimation of the model (Becker et al., 2021). Overall, the classification results showed that a Random Forest (RF) approach performed the best, whilst Naïve Bayes (NB) consistently performed the worst. This pattern could be attributed to the nature of NB as this is a parametric algorithm. These types of algorithms are better suited to simple classification problems — unlike ours — in which initial assumptions are made about the shape (or functional form, f) of the data (usually that it is linear (James et al., 2015)). Given the complexity of our classification problems, we did not make explicit prior assumptions about the shape of the data, in line with the characteristics of non-parametric algorithms such as RF (James et al., 2015).

In terms of detecting mood, the classification analysis demonstrated that the Random Forest (RF) models were again superior in discriminating between EA (Table 1) and HT (Table 2) across all performance measures. More specifically, this algorithm was able to correctly identify more positive “high” EA/HT instances with fewer false negatives. Further statistical tests demonstrated that the accuracies obtained were all significantly above chance for EA (Table 1) and HT (Table 2).

Importantly, these results represent considerable improvement over previous research (Bautista-Salinas et al., 2019; Opoku Asare et al., 2022; Sano et al., 2015; Zhang et al., 2020). In the case of (Sano et al., 2015), skin temperature and EDA was collected from a wrist-worn device in everyday life with SVM accuracy of approximately 0.78 for the binary detection of perceived stress. Meanwhile in (Bautista-Salinas et al., 2019) the E4 device was used to collect similar data for detection of mood in the elderly with accuracy ranging from 0.7 – 0.8. However, the study only included four participants and so generalisability of its findings is unclear. Additionally, (Opoku Asare et al., 2022), mood scores (valence and arousal), smartphone and wearable sensor data were collected in everyday life to predict depression. Our findings compare favourably with previous models, which have had at best 0.59 F1 Score and 0.50 sensitivity using mood and wearable device data within an XGBoost model (Opoku Asare et al., 2022). We also demonstrate improvement over (Zhang et al., 2020) who also used the Empatica E4 device and excluded datapoints equal to the mean in their binary detection of valence-arousal to achieve accuracies between 68.15 % – 76.37 %. Our work represents substantial improvements of F1 Score results that improved between 37 % and 42 % and increased sensitivity between 62 % and 70 % over previous work.

In detecting feelings of general social connection (Q1), the RF model again discriminated best between higher and lower social connection

(Table 3). Similar to the mood findings, RF was able to recognize more positive “high” instances of social connection and fewer false negatives. Further statistical tests confirmed that the accuracies obtained were all significantly above chance and that all the models were significantly different to each other (Table 3). Measuring social connection using physiology in the real world has not been undertaken before and so making direct comparisons on the basis of this work is challenging. As loneliness is seen as the inverse of social connection, such studies provide our closest comparison. Nevertheless, such studies have mainly used smartphone data with limited wearable device data, and thus, our findings represent a clear improvement in accuracy of detection on these. For instance, previous research has reported accuracies of 0.80 for the binary detection of loneliness when using features from a smartphone, whilst wearable Fitbit Flex 2 device data resulted in accuracies of 0.68 (Doryab et al., 2019). Another study used smartphone data from 12 older adults over a week and demonstrated an accuracy of 0.67 in the detection of social loneliness (Sanchez et al., 2015). The present findings thus reflect an identification improvement of between 19 % and 21 % over previous work.

Again, the RF model outperformed the other algorithms in the detection of social density (Table 4) and sense of connectedness to other people within a 5 m vicinity (Table 5). Further statistical tests confirmed that the accuracies obtained were significantly above chance, apart from SVM, but all the models were significantly different to each other. Measuring those within the immediate vicinity has not been undertaken before in this manner, with previous work often utilizing Bluetooth to determine the proximity of others or social context, which is distinct from social connection (Bauer and Lukowicz, 2012; Mäder et al., 2024; Meegahapola et al., 2021; Wu et al., 2021). Social context refers to environmental and situational factors surrounding an interaction and mainly captures whether someone is alone or not (Mäder et al., 2024; Meegahapola et al., 2021). In contrast, social connectedness refers to a feeling of belonging and subjective bonding that people have to relation to others, and this goes beyond whether they are alone or not (Haslam et al., 2015). For instance, one study (Wu et al., 2021) drew on smartphone Bluetooth and location data from 129 university students over three weeks, predicted momentary loneliness with a maximum AUC of 0.74 using RF. A limitation of these data is that they rely on Bluetooth being activated on other people’s devices. We are unaware of any other studies that have utilized only physiological data to detect proximity and/or feelings of social connection to others in their vicinity. A key advance in our work is thus the inclusion of a wider range of physiological data. For while Bluetooth and GPS can offer contextual information (e.g., about places visited), understanding the physiological processes that are associated with these experiences is also important.

Mood, loneliness, and feelings of social disconnection are complex feelings that can manifest at any time – e.g., you can still feel lonely or have low mood whilst being in a room full of people (Green et al., 2018). This paper works towards addressing this challenge of detecting such instances as the findings of this study support the use of wearable devices and physiological features in objectively detecting mood and in-the-moment social connection, as well as social density estimation, in everyday settings. The results of this paper are important to inform intervention design and thus have implications for advance in the fields of affective computing, lifelogging, and social and health psychology. From a technological point of view, the work demonstrates how complex signals can be collected in everyday activities and processed to produce better detection accuracy using a random forest machine learning approach. The work also demonstrates how complex psychological states can be detected using only wearable devices that home in on the physiological features that are the most discernible correlates of social connection. This work has implications for longer term health, and particularly in helping identify objective markers of those who might be at risk of loneliness and social disconnection — states which are known to be more frequent in periods of life change (Haslam et al., 2021) and have an adverse impact on health and well-being (Doryab et al., 2019).

This would be especially useful in contexts where social connectedness is threatened (e.g., as it was in the context of social distancing restrictions that prevailed during COVID-19). The lightweight framework we implemented, which is unobtrusive for the user to wear, also provides opportunities for longitudinal studies to further explore this area.

5.1. Limitations and future work

Although these results are promising, this research is not without limitations. In particular, the distribution of general feelings of social connection (Q1) in Fig. 5 revealed very little variance. This reflects characteristics of the participant sample as the present sample comprised healthy young people drawn from the general population rather than from a clinical setting and so who were not specifically recruited for their vulnerability to stress or loneliness, and who were monitored in a university setting. Most were university undergraduate and postgraduate PhD students. While this reflects a deliberate focus on a non-clinical, ecologically valid population, there are drawbacks about the generalizability of our findings. Another limitation of this study stems from ethical considerations to not overburden participants by restricting data collection to working hours. Specifically, this included an inability to collect data overnight. Accordingly, the study was conducted between 9am to 5pm, with the subjective reports being collected at the same time each day. These constraints were necessary for participant welfare and comply with institutional ethics guidelines. However, this can be seen as both a strength and a limitation; whilst this method did limit time of day, it also reduced sources of random variation (noise) and increased the chance that participants may be involved in similar activities around the same time each day, given the university context, as loneliness has been found to be linked with greater day time dysfunction (Mushtaq et al., 2014). Future work, though, should look to address this limitation through use of alternative methodologies that monitor individuals throughout the whole day, while maintaining rigorous ethical standards. It would also be beneficial to seek to extend the present study by tracking a wider range of individuals (e.g., older adults, members of vulnerable populations, young professionals, etc.) in an array of contexts (e.g., from university to home, and in the general community), for a longer duration (e.g., of weeks not just days) and over longer time points (not just between 9am and 5pm). A more targeted recruitment strategy would allow the robustness of the findings to be evaluated under more heterogeneous conditions. Nevertheless, as a first step, the results demonstrate that wearable sensors measuring physiological signals can capture variation in mood and perceived social connectedness in naturalistic, everyday settings.

6. Conclusions

The motivation of the study was to explore the possibility of using wearable sensors to improve our ability to objectively assess mood and social connection. To this end, physiological features were extracted from a wearable device that recorded these affective states. Our findings show that perceived social connectedness, which is a complex social emotion, can be detected using wearable devices in everyday life. This provides an important advance in identifying physiological correlates of affect and social connectedness, which can be obtained in a relatively straightforward manner using everyday technology. These complex psychological states are a major focus of contemporary research interest, and accordingly, the present insights should be of practical use not only to researchers who are seeking to better understand the causes, configurations, and consequences of loneliness in everyday life but also to practitioners who are seeking to manage and reduce it (e.g., (Cruwys et al., 2021; Haslam et al., 2019, 2016)).

CRedit authorship contribution statement

Chelsea Dobbins: Writing – review & editing, Writing – original

draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stephen Fairclough:** Writing – review & editing, Methodology, Conceptualization. **Catherine Haslam:** Writing – review & editing, Methodology, Conceptualization. **S. Alexander Haslam:** Writing – review & editing, Methodology, Conceptualization. **Sarah Bentley:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Tuned hyperparameters for the Random Forest (RF) algorithm for all models, per outer fold

Model	Number of Features	Threads	Trees	Classification Error
EA	7	17	20	0.17
	17	10	12	0.17
	17	5	16	0.16
	10	17	15	0.18
	9	7	14	0.19
HT	11	7	10	0.23
	25	19	13	0.20
	11	3	15	0.20
	32	16	17	0.21
	12	14	19	0.17
General Social Connection (Q1)	16	10	17	0.20
	16	3	15	0.20
	27	8	10	0.19
	33	7	19	0.19
	15	8	20	0.20
Social Density (Q2)	19	9	17	0.19
	27	19	17	0.19
	33	9	15	0.20
	33	9	14	0.20
	30	8	17	0.19
Proximity Social Connection (Q3)	22	10	20	0.16
	34	9	14	0.18
	20	19	12	0.17
	10	5	14	0.18
	34	6	15	0.17

Appendix 2. Tuned hyperparameters for the k-Nearest Neighbour (kNN) algorithm for all models, per outer fold

Model	Number of Features	k	Distance	Classification Error
EA	14	12	4	0.30
	18	11	2	0.27
	21	16	2	0.28
	4	12	3	0.31
	13	15	5	0.30
HT	34	17	1	0.25
	3	10	3	0.29
	13	19	3	0.33
	15	20	1	0.30
	6	3	4	0.27
General Social Connection (Q1)	14	11	1	0.27
	19	5	2	0.27
	13	4	3	0.29
	27	16	1	0.23
	22	9	1	0.22
Social Density (Q2)	27	3	2	0.28
	12	19	2	0.28
	10	10	5	0.30
	23	14	1	0.23
	16	15	1	0.23
Proximity Social Connection (Q3)	8	13	1	0.26
	32	19	1	0.22
	4	6	1	0.24
	17	13	1	0.20
	27	14	1	0.21

Appendix 3. Tuned hyperparameters for the Support Vector Machine (SVM) algorithm for all models, per outer fold

Model	Number of Features	Cost	Gamma	Kernel	Degree	Classification Error
EA	23	-3.37	-4.74	polynomial	4	0.43
	9	14.30	1.76	radial	NA	0.29
	14	7.12	-3.92	radial	NA	0.33
	17	-13.94	3.23	polynomial	3	0.43
	12	-7.23	0.35	radial	NA	0.42
HT	10	13.91	-5.90	radial	NA	0.39
	27	-0.33	-1.35	radial	NA	0.30
	8	-6.20	1.68	radial	NA	0.40
	35	7.25	-0.61	radial	NA	0.33
	22	0.99	9.59	radial	NA	0.47
General Social Connection (Q1)	31	-4.81	-5.60	radial	NA	0.44
	22	-6.73	-5.61	radial	NA	0.44
	34	11.01	-4.55	polynomial	4	0.42
	10	-6.93	-4.71	radial	NA	0.45
	26	-5.90	0.50	polynomial	3	0.37
Social Density (Q2)	39	-5.00	9.59	polynomial	4	0.40
	17	9.18	-3.25	polynomial	2	0.48
	26	5.25	-0.92	radial	NA	0.26
	30	-5.59	-0.83	radial	NA	0.44
	13	0.96	-1.94	radial	NA	0.37
Proximity Social Connection (Q3)	28	3.80	7.75	radial	NA	0.46
	2	11.62	12.02	radial	NA	0.35
	37	-14.17	-3.54	radial	NA	0.50
	35	4.46	7.11	polynomial	3	0.43
	32	-7.00	-2.31	polynomial	2	0.41

Appendix 4. Tuned hyperparameters for the Naïve Bayes (NB) algorithm for all models, per outer fold

Model	Number of Features	Classification Error
EA	8	0.47
	21	0.46
	24	0.47
	7	0.47
	17	0.47
HT	33	0.47
	19	0.47
	34	0.47
	28	0.47
	34	0.47
General Social Connection (Q1)	31	0.45
	33	0.45
	38	0.44
	24	0.45
	37	0.44
Social Density (Q2)	5	0.45
	10	0.45
	1	0.44
	10	0.45
	5	0.44
Proximity Social Connection (Q3)	9	0.43
	17	0.43
	10	0.43
	26	0.43
	28	0.44

Data availability

Data will be available on request by emailing the corresponding author.

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