An Interview Study for Developing Subjective Measures to Record Self-Reported Mood in Older Adults: Implications for Assistive Technology Development

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Abstract

Increased life expectancy has led to a 15% growth in the population of seniors (aged 65 and above) in Canada, in the last 5 years and this trend is expected to grow. However, the provision of personalized care is bottlenecked, due a severe shortage of formal caregivers in the healthcare industry. Technological solutions are proposed to supplement or replace human care, but have not been widely accepted due to their inability of dynamically adapting to user needs and context of respective situations. Affective data (i.e., emotions and moods of individuals), can be utilized to induce context-awareness and artificial emotional intelligence in such technological solutions, and thereby provide personalized support. Moreover, the capacity of brain to process affective phenomenon can serve as an indicator of onsetting neuro-degenerative diseases. This research thoroughly investigated what affect is, and how it can be used in computing in real-life scenarios. Particularly, evidence was obtained on which biological signals collected using a wearable sensor device were capable of capturing the arousal dimension of affective states (emotions and moods) of individuals. Furthermore, a qualitative study was conducted with older adults using semi-structured interviews, to determine the feasibility and acceptability of different self-report measures of mood, which are crucial to capture the valence dimension of affect. As the hypothesis that older adults would prefer a pictorial measure to self-report their mood failed, we proposed an adjective-based mood reporting instrument prototype, and laid down implications for future research.

Thesis outline

This thesis has been structured into 5 chapters:

Chapter I introduces the topic of this thesis, provides a brief overview of the research problem, and lists out the definitions for the key concepts used in this thesis. **Chapter II** contains a thorough discussion on relevant literature and specifies the objectives which were investigated in this research. **Chapter III** describes the methodology for analysing publicly available quantitative data relevant to the research, with a discussion on the results obtained from the analysis. **Chapter IV** describes the methodology for conducting a qualitative study, and discusses the results obtained from my research. **Chapter V** concludes the thesis with a summary, a proposed prototype instrument, and recommendations for the future work.

Chapter I: Introduction

The advancements in healthcare and medicine have increased human longevity, and the world is experiencing a demographic transition in the aging population. According to the data [1] published by Statistics Canada (as of July 1st, 2022), the population of seniors (adults 65 years and older), has seen a 15.34% growth in the last 5 years, with the current tally slightly exceeding 7.3 million (Figure 1).

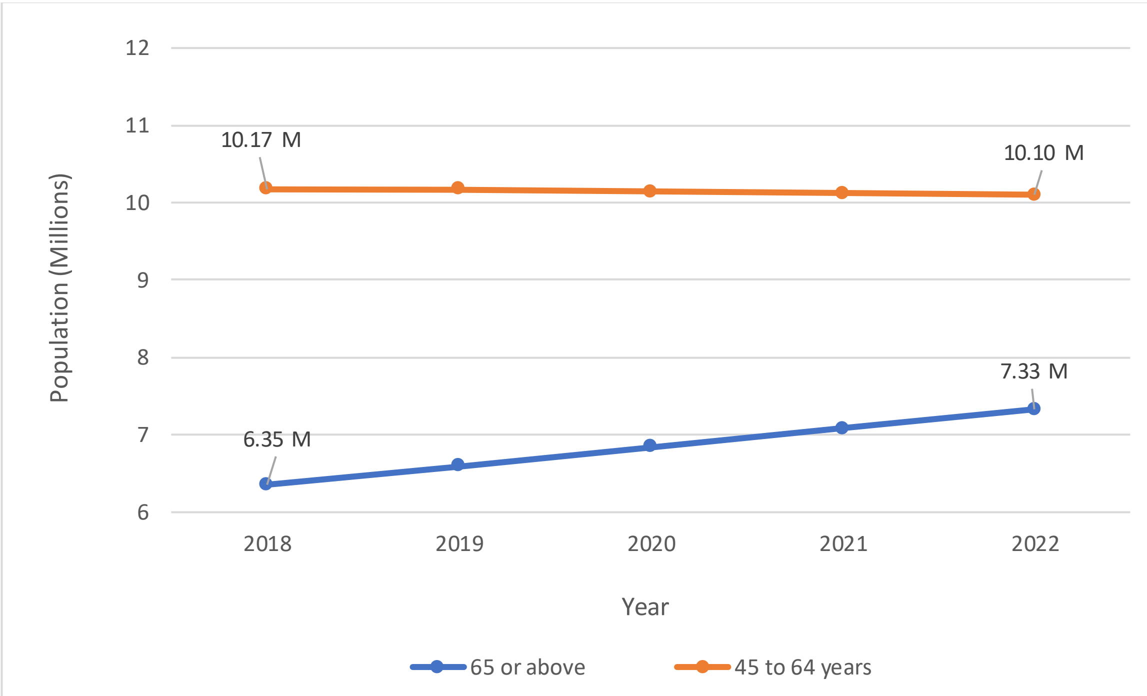

Figure 1: Population for two age groups (in last 5 years). Figure generated from the data published by Statistics Canada [1]. The first and last data points are approximately labelled to two decimal places.

Older adults, even when limited by physical and health constraints, aspire to age in their own home and community for as long as possible [2], although external care is often required to support the gradual decline of functional and cognitive capabilities with age. The majority of eldercare in Canada (75%) is provided by individuals in the age range of 45 to 64 years [3], but in the last 5 years, this population (45 to 64 years) has declined by 0.67% (Figure 1) [1]. Moreover, Canada faces a severe shortage of trained (formal) caregivers, and even though

93% of elders live in their private homes, long-term care facilities still have to rely on informal (friends and family) care providers to support their residents [4]. This not only reduces the quality of care received by the elderly, but also affects the physical, mental, social, and financial aspects in the life of informal caregivers, ultimately leading to deterioration in their quality of life [4]. As the provision of eldercare deteriorates both in terms of quality and quantity, it is imperative to find solutions which either supplement, or completely substitute the traditional care system.

The interdisciplinary field of gerontechnology (gerontology + technology) [5], concentrates on developing technologically-based services, products and environments to aid the aging and aged adults [6]. Ambient assisted living (AAL) technologies, which are the core focus of gerontechnology, aim to prolong the active and independent lifestyle of older adults by assisting them in performing activities of daily living (ADL), typically in a smart environment (consisting of an internet of wireless sensors, actuators, and interfaces which are powered by ambient intelligence) [5]. Moreover, AAL systems carry the potential to monitor the decline in cognitive health of an aging individual by detecting changes in behavioural patterns [5], and thus, to predict the onset of neuro-degenerative diseases [7].

Despite their potential benefits, the scientific evidence for effectiveness of AAL systems is weak [8], and barriers such as “lack of human interaction” hinder the mainstream adoption of AAL technologies [9]. To be able to deliver appropriate and personalized assistance, and to replicate human-human interactions, it is crucial that the AAL technologies exhibit context-awareness [10], i.e., are able to comprehend any situation in the context it occurs without a user’s explicit intervention [11], and are smart enough to adapt to the changing needs and behaviours of the end-users [12].

“One of the most important cognitive behaviors in humans is expressing and understanding emotions” [13], and the ability to detect, recognize and interpret how a person feels, as well as to adapt and respond appropriately to it can induce artificial emotional intelligence in AAL systems [14], leading to natural, trustworthy and efficacious HCI [15], thereby increasing the mainstream acceptability of such technologies. Moreover, proper regulation of emotions has been acknowledged as a crucial resource in aging, as it "allows individuals to successfully deal with the challenges and limitations imposed by the physiological aging process" [16], and declining mood trajectories in older stages of life (over the age of 71), can indicate diminishing white matter microstructure [17], which is hypothesized to negatively affect cognitive functionalities [17]. Similarly, an interdependency between depressed mood, frailty and disability has been discovered in a longitudinal study [18]. Therefore, studying daily affective experiences (emotions and moods) of the aging population could be vital in promoting healthy aging.

This thesis aimed to investigate the acceptability and feasibility of including self-report instruments of mood change in the research and development of AAL solutions, so that the affective experiences collected from the daily lives of older adults (using objective and/or subjective measures) can be leveraged to enhance the context-awareness of assistive technologies, thus, leading to appropriate and personalized care.

Key concepts, abbreviations, and terminologies

Activities of daily living (ADLs): Daily self-care activities performed by individuals.

Affective Mediation: "Computer-based technology that enables the communication between two or more people displaying their emotional states" [19].

Ambient Intelligence (AmI): Ambient intelligence refers to "the concept of a smart environment sensitive to its inhabitants, able to support them in an unobtrusive, interconnected, adaptable, dynamic, embedded, and intelligent way, and even capable of anticipating their needs and behaviors" [20].

Context: "Any information that can be used to characterize the situation that is relevant to the interaction between the users and the system" [10].

Eldercare: Providing services to older people (greater than 65 years of age), to live comfortably and independently.

Emotional Intelligence: "A facet of human intelligence that includes the ability to have, express, recognize, and regulate affective states, employ them for constructive purposes, and skillfully handle the affective arousal of others" [15].

Emotions: "Emotions are high-intensity, specific feeling states that are typically short-lived, have identifiable antecedents, are directed at a particular object, and direct ongoing thoughts and behaviours" [21].

Exploratory data analysis: Investigation of dataset(s) to discover patterns and find anomalies.

Formal caregivers: Caregivers that have received professional training for providing care and are paid for their services.

Informal caregivers: Unpaid care givers, constituting typically of family members.

Internet of Things (IoT): Network of sensors, software, and similar technologies, typically employed for automatically collecting, processing, and transmitting data.

Mood: “Moods are low-intensity, diffuse feeling states that can last for hours or days, have a gradual onset with cumulative antecedents, are directed at the world as a whole, and have a global and pervasive influence on one’s perception and motivation” [21].

Order bias: Influence of the order of items/questions on the responses of participants.

Perley Health: Long-term care centre in Ottawa for seniors and veterans.

Physiological signals: Electrical measurements taken from physiological processes of humans such as heart beats, respiration, and body current signals.

PII: Personally Identifiable Information.

Sampling Rate: Number of samples collected in one second.

Chapter II: Literature Review

Ambient Assisted Living Technologies

Ambient assisted living (AAL) technologies have been defined as services, products and systems which utilize the information and communication technologies (ICT), to provide the vulnerable and older adults with "intelligent, unobtrusive and ubiquitous support" [5]. The goals of AAL systems include, but are not limited to: enabling independent living and aging in place [22], supporting elders with the activities of daily life (ADLs) [22], cultivating a secure and healthy environment [22], reducing the costs of healthcare [5], and increasing connectedness with peers as well as informal caregivers [22].

Evolution of AAL technologies

According to Blackman et al. [5], the AAL technologies have evolved over three generations:

1. The first generation of AAL technologies [5] included wearable devices (such as alarm or response buttons) which had to be triggered manually by the user. These were particularly useful in emergency scenarios where immediate assistance was required, such as in case of a fall, provided that a user was wearing them. However, the first generation of AAL technologies were not applicable in high-risk scenarios where a user could be mentally or physically incapacitated to activate the alarm.
2. Building upon the limitations of the first generation, the second generation of AAL technologies [5] consisted of sensor devices which monitored hazardous scenarios in the physical environment, such as the stove being left on for a long time, and responded automatically to it, without needing any manual intervention.
3. The third generation, which presently is being researched and developed, focuses on integrating the wearable devices and home monitoring sensors, in an unobtrusive fashion, to create an ambiently intelligent living space [5].

Expanding on the third generation of AAL technologies, Byrne et al. [23] acknowledged a lack of a clear taxonomy in and proposed a classification framework for AAL technologies, dividing them into four core categories, namely: "smart homes, intelligent life assistants, wearables and robotics". Similarly, Cicirelli et al. [7] discussed four principal categories of AAL technologies, which were:

1. Wearable Sensors [7]: Miniaturized and energy efficient sensor devices worn on the body, that enable continuous monitoring of behavioural, biological, and environmental data. E.g., smartwatches, smart textiles.
2. Smart Everyday Objects [7]: Daily life objects such as home appliances equipped with communicative and interactive capabilities, based on the principles of Internet of Things (IoT). These devices collect information on the activities of daily life and interaction with the environment. E.g., mattress equipped with sensors to detect quality of sleep.
3. Environmental Sensors [7]: Devices that detect changes in environmental parameters such as the air quality or temperature. These devices are placed discreetly in the surroundings without modifying existing home objects and are useful to determine and prevent adverse consequences due to environmental hazards. E.g., thermostat monitoring the temperature of a kitchen to detect fire.
4. Social Assistive Robots [7]: Robots employed to "support and enhance human activities", such as lifting heavy objects or automatically performing repetitive tasks.

Need for context-awareness in AAL and the role of affective data

The research work conducted on the everyday use of information and communication technologies by older adults has revealed that the "elderly are less likely to have access to and use ICT in their daily activities" [24]. Low acceptance has been attributed to the fact that most of the AAL solutions released to fulfil the needs of older adults are believed to be straightforward fixes, based on the assumptions that "needs" generate from underlying illnesses, losses, and dependencies [5]. Furthermore, the AAL technologies are developed by keeping an average user in mind (i.e., with a 'one size fits all' approach), whereas the actual user quite often differs from the average user in terms of specific needs, patterns of interaction, and cognitive, emotional, perceptual, and behavioural capabilities [25]. These "straightforward" solutions, however, fail to take into consideration the preferences of end-users, the context in which the needs are experienced and the impact they (the solutions) have on day-to-day life [5]. Moreover, barriers such as "lack of human interaction" hinder the mainstream adoption of AAL technologies [9].

To deliver appropriate and personalized assistance, it is crucial that the AAL technologies exhibit context-awareness [10], i.e., are able to comprehend any situation in the context it occurs without a user's explicit intervention [11], and are smart enough to adapt to the changing needs and behaviours of the end-users [12]. Context has been defined as "any information that can be used to characterize the situation that is relevant to the interaction between the users and the system" [10]. Prior research on human-computer interactions (HCI) to interpret the context of human activities was based on the W4 formalization (*what, where, when, who*) [10], [26], but was limited to only addressing the "apparent perceptual aspect of human behaviour" [26]. To include the cognitive aspects while trying to interpret human activities [26], and transform HCI to intelligent HCI (IHCI), the W4 formalization was extended to the W5+ formalization of context (*what, where, when, who, why, how*) by asking the additional *how* and *why* questions [10], [26].

Therefore, theoretically, multi-modal input streams from environmental and behavioural signals of users can be employed to train the AAL technologies to be context-aware [10]. Although, the contextual information of the surroundings (such as temperature) is easy to acquire by deploying sensor devices (thermostats etc.), a user's context can range from static information (such as their demographics and medical history) to dynamic information (such as their position in 3-dimensional space, or their vital signs such as heart beat, etc.) [11], and can be difficult to frequently acquire due to limitations of old age.

Nonetheless, the 'how a person feels' aspect of the W5+ context formalization can be accurately captured by obtaining an individual's affective data (i.e., their feelings, emotions, and moods); and the ability to sense, adapt and respond to the affective states of users can make AAL systems more natural, trustworthy and efficacious [15], thus enhancing human-computer interactions. In addition to personalizing assistance, the awareness of a user's activities, routines and affective factors could improve an AAL system's abilities for inferring the situations in which emotions naturally occur [27], thus contributing towards the context-awareness.

What is affect?

J.A. Russel [28] defined "core affect" (commonly identified as a "feeling"), as a consciously experienced, primitive neurophysiological state that can be experienced without any stimuli and "is irreducible to anything else psychological". Moreover, core affect is constantly experienced, although it fluctuates in intensity and nature over time [29]. Comparably, D. Handayani et al. [30] defined the word "affect" as a superordinate category, which encompasses a broad range of feelings experienced by humans; and often serves as the denominator for both mood and emotion.

Psychological description of affect

Building upon the research in affective psychology, Posner et al. [31], explained affect using the Russel's "circumplex model of affect" [32] and stated that "all affective states arise from two independent neurophysiological systems", called valence (pleasant-unpleasant) and arousal (activated-deactivated), and "each and every affective experience is the consequence of a linear combination of these two independent systems". This has been depicted in the Figure 2.

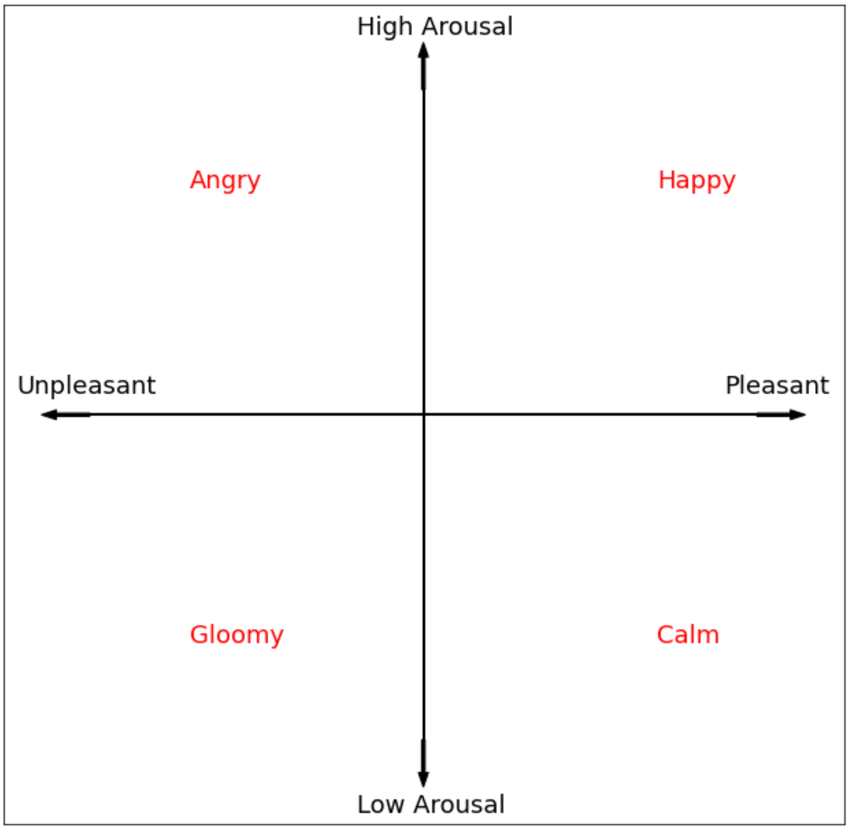

Figure 2: Russel's two-dimensional model of affect (black-solid lines), along with one affective state respective to each quadrant (red). The figure is inspired and redrawn and from the information available in [31].

Watson and Tellegen [33], also arrived at a two-dimensional model of affect, by performing factor analyses on intra- and inter-individual self-reported data [34]. The authors labelled one of the axis as "Positive Affect", which ranged from "high-activation pleasant affect" to "low-activation unpleasant affect" [34]. The second axis was labelled as the "Negative Affect", and ranged from "high-activation unpleasant affect" to "low-activation pleasant affect" [34]. Initially (in 1985), the "basic compatibility" of this model with the Russel's model of affect [32] was recognized by Watson and Tellegen, but in 1997, Watson and Clark restated that the two models represented "rotational variants of each other" [34]. This has been depicted in the Figure 3.

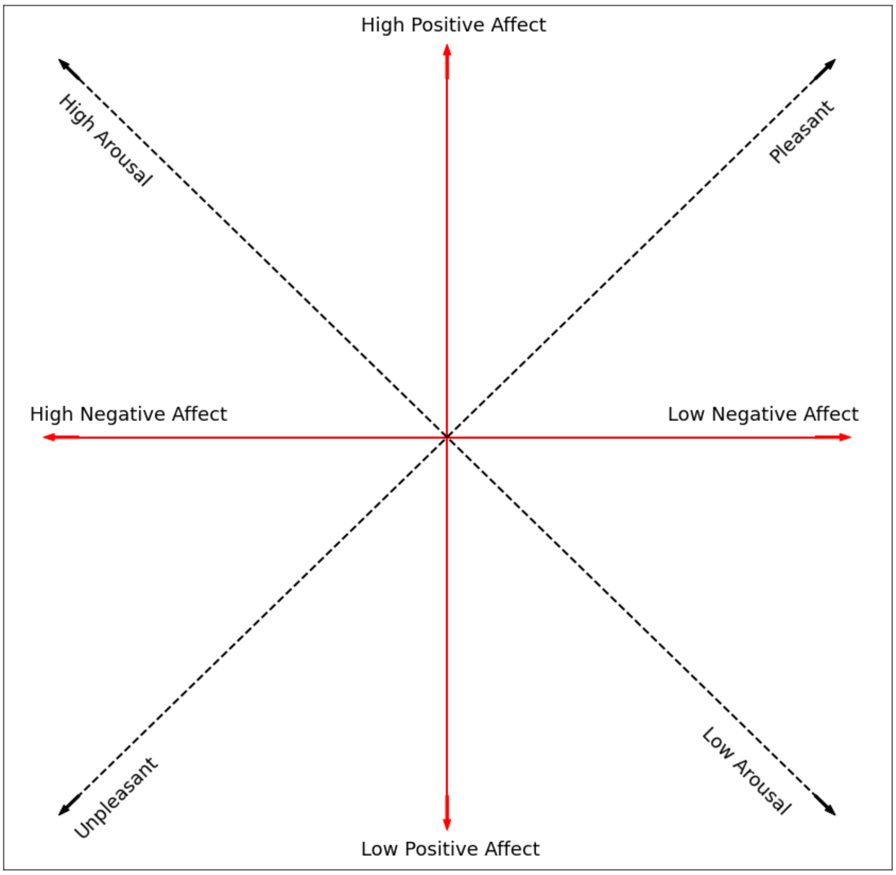

Figure 3: Modified and redrawn, based on Figure 3.3 in [34], which provides a side-by-side comparison with a "45° rotation of axes" between the Russel's two dimensional model (in black-dotted lines above) and Watson and Tellegen's (in red-solid lines above) two dimensional model; depicting the fact that the given models are "rotational variants of each other" [34].

Additionally, models with a third orthogonal dimension appended to the valence-arousal to depict the potency or "dominance" of the affective phenomena were proposed [34]. However, the potency factor was eliminated as it indicated a cognitive perspective of the affective experience, rather than the affect itself [34]; which further led to "consolidation" of the valence-arousal two-dimensional model [34].

Biological description of affect

Neurologically, the affective states are accompanied by characteristic physiological responses, which occur involuntarily and are "impossible to control for humans" [35]. These physiological responses are directed by the autonomic nervous system (ANS), which further separates into the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) [35]. The PNS "controls the body's involuntary responses at rest" [36], such as regulating digestion, and is associated with decreased heart rate and decreased respiration rate [35]. In contrast, the SNS "controls the body's involuntary responses to a perceived threat" [36], and delivers energy by increasing physiological parameters (such as the heart rate, respiration rate, electrodermal activity, muscle activity, and adrenalin release) [35].

Furthermore, the mesolimbic system of the brain (associated with processing pleasure and reward) is considered to be responsible for the "valence-neural circuitry", whereas the "arousal-neural circuitry" is thought to be regulated by the reticular formation (RF) networks [31]. Cognitive interpretation of the neurophysiological signals received from mesolimbic and reticular networks, is done in the prefrontal cortex [31], which also takes into account the "temporal contingencies that link prior experiences of stimuli within varying life contexts with expectations for the future" [31].

Types of affect: Emotion and Mood

As stated earlier, "affect" has been defined as a hypernym term, which encompasses a broad range of feelings experienced by humans; and often serves as the denominator for both mood and emotion [30]. In spite of being used interchangeably, even in the scholarly literature, the terms "mood" and "emotion" specify unique and distinct phenomenon [21] [37]. Therefore, it is important to provide clarification to distinguish between these terms, before proceeding on to the construct that was chosen for this research. Table 1 constructed from [21] and [29] distinguishes between the two components of affect: mood and emotion, in detail:

Mood	Emotion
Exists for longer durations (hours/days) [21]	Exists for short durations (seconds or minutes) [21]
Has low intensity [21] (exceptional in clinical cases [29])	Has high intensity [21]
The object of appraisal is not easily identifiable [29], but mood is considered as a "response to cumulative causes" [21]	Triggered by a specific stimulus [29], and is considered as a "response to a single cause" [21]

Has a gradual onset and is present continuously [21]	Has a rapid onset and is present only episodically [21]
Globally influences an individual’s responses and shapes their “ongoing thought and behaviour” [21]	Targets a “specific adaptive response” by directing/redirecting and individual’s thought and behaviour” [21]
Exhibits a mild impact on physiological signals [21]	Exhibits a strong impact on physiological signals [21]

Table 1: Distinction between mood and emotion

Also, the patterns of mood are divided into “traits”, which remain stable, and “states” which are “relatively transient” [38]. The mood traits reflect the tendency and capacity of a person to experience negative or positive moods [38]. Having genetic origins, mood traits tend to remain constant throughout a person's life, whereas mood states vary considerably over time, irrespective of the mood traits of the person [38]. In this research, the term ‘mood’ denotes mood states.

Regardless of their differences, mood and emotion are not independent, instead they “dynamically interact with each other” [21]. Moods can “lower the threshold of emotional arousal” (e.g., a person in irritable mood becomes angry easily), and “accumulation of emotions can lead to particular moods” [21]. To visualize this relationship, I’ve created a Venn diagram, represented in the Figure 4, where the universal set is represented by “affect”, which encompasses both mood and emotion [30], and the intersection between mood and emotion shows their influence on each other [21].

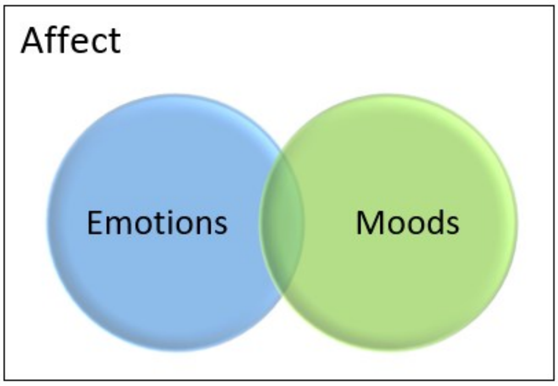

Figure 4: Relationship between affect, emotion, and mood based on [30] and [21].

How is affect detected?

To study affect, two approaches have been described in the literature. The first is subjective evaluation using self-report methods by the individuals themselves, and the second is automatic recognition and inference of affect on the basis of objective signals (behavioural and physiological).

Subjective well-being refers to "a person's subjective evaluation of their quality of life as a whole" [39], which is unique for every individual depending on their circumstances and experiences in life. According to Steptoe et al. [40], there are three distinctive aspects of subjective well-being: eudemonic well-being (sense of purpose in life), evaluative well-being (overall satisfaction in life), and hedonic well-being (moods or feelings). Monitoring of hedonic indicators [41] can help to regulate an individual's emotions, predict positive affect, vitality, and carefreeness. Lucas [39] stated that self-report measures are a necessity for evaluating a person's subjective well-being, as only an individual would be able to assess their life to the full extent. Moreover, [39] stated that affective components of subjective well-being differ from the cognitive components (life satisfaction), which require conscious reflection on life; and should therefore be measured separately (and not globally). The utility of these conceptualizations has been demonstrated in research on self-report measurement of psychosocial impact of assistive technology devices, in studies that identified affect and emotions as critical components in predicting the adoption and use of these devices [42] [43].

The main advantage offered by self-report methods is their ability to capture "subtle and distinct mood types" [21]. However, such methods are generally time-consuming, cognitively taxing, and are limited in naturalistic settings (such as while performing ADLs), as respondents have to interrupt their on-going activities and divert their attention towards self-reporting [21]. A solution to these limitations is offered by automatic affect recognition.

According to Gonzalez-Sanchez et al. [36], automatic affect recognition is as a two-step process. In the first step an individual's behavioural or physiological signals are collected using sensor devices [36]. The second step is to process the collected data by applying machine learning algorithms to deduce the underlying affective states [36]. In case of data being accumulated from multiple sensors, a third step is required for integrating the information, which could be done by either accumulating raw collected signals before processing, or integrating the analysed data post processing [36]. AlZoubi et al. [44], elaborated on the different modalities that are used to detect affect, which are described in the Table 2.

Modality [44]	Abbreviation [44]	Type of modality [45]	Description [44]
Emotional speech	-	Behavioural	Detection of affective states using patterns of speech (such as the speech rate).
Facial expressions	-	Behavioural	Interpreting facial features recorded in videos or images to derive affective states.
Body posture and gestures	-	Behavioural	Analysing body posture and gestures to infer affective behaviour.
Electroencephalogram	EEG	Physiological	Electrical activity signals from the brain.
Electrocardiogram	ECG	Physiological	Electrical activity of the heart over a period of time.
Blood Volume Pressure	BVP	Physiological	Pressure exerted by the blood flow on the blood vessels.
Galvanic Skin Response (also known as) Electrodermal Activity	GSR or EDA	Physiological	Electrical conductance of the skin.
Electromyogram	EMG	Physiological	Electrical signals from muscular activity.

Respiration	RESP	Physiological	Breathing rate (Inhalation/exhalation)

Table 2: Physiological and behavioural modalities used to detect affect automatically.

It is important to note that humans are capable of effectively controlling their behavioural modalities, which in turn depend upon an individual's personality and their current environment [45]. In contrast, the physiological signals cannot be intentionally controlled and exist continuously [45], irrespective of personal and environmental variables. Therefore, physiological modalities are advantageous over behavioural ones, for the purpose of automatic affect detection; assuming that physiological changes are as reliably associated with specific emotional reactions as are facial expressions.

Two of the physiological signals (EDA and BVP) mentioned in Table 2 are discussed thoroughly in the following paragraphs, as they would later be used in Chapter III.

Discussion on the Electrodermal Activity (EDA)

Electrodermal activity is defined as the "continuous variation in the electrical characteristics of the skin" [36], which is measured either as the resistance (by supplying constant current) or as the conductance (by supplying constant voltage) between two electrodes placed on the skin [35], generally at locations of high sweat gland density, such as the fingers or the wrists. It is argued that EDA is "the only autonomic psychophysiological variable that is not contaminated by parasympathetic activity", and therefore, "arguably the most useful index of changes in sympathetic arousal" [46].

EDA can further be decomposed into two parts: the rapid phasic components (also called Skin Conductance Responses (SCRs)) and the background tonic response (also called the Skin Conductance Level (SCL)) [46]. The tonic-level of EDA corresponds to the "slower acting components and background characteristics of the signal (the overall level, slow climbing, slow declinations over time)", whereas, the phasic component corresponds to the "faster changing elements of the signal" [46].

Discussion on the Heart Rate Variability and Blood Volume Pulse (BVP)

A bundle of specialized cells, called the sinoatrial (SA) node, generate electrical impulses which initiate heartbeats [47]. The SA node is in turn controlled by complex interactions between mechanical activities (e.g., respiration) and different regulatory systems (such as the autonomic nervous system) [47]. The variability in heart rate (HRV) serves as an "indicator of the dynamic interaction and balance between the sympathetic and parasympathetic systems" [48], and is a potential indicator of onset and offset of different affective states. Specifically, the sympathetic (SNS) contributions (such as response to stress) are reflected by the low-frequency (LF) power spectrum (0.04 to 0.15 Hz) of the HRV, whereas the high-frequency (HF) power spectrum (0.15 to 0.5Hz) indicates restful states and is dominated by parasympathetic nervous system (PNS) [49]. Therefore, the ratio of LF to HF is commonly used to measure the balance between the SNS and PNS [49].

The heart rate variability (HRV) is derived by processing either of the blood volume pulse (BVP) waveforms or the electrocardiogram (ECG) waveforms, which are collected using photoplethysmography (PPG) and electrocardiography respectively. Electrocardiography utilizes conductive pads (electrodes) placed on the chest to measure the electrical activity of the heart, whereas photoplethysmography deduces the cardiac activity by detecting changes in blood volume, using non-invasive optical sensors [50]. The optical sensors measure the "changes in the attenuation of light energy in its pathway when transmitted or reflected in tissues and bloodstream", which correlate with the systolic and diastolic phases of the cardiac cycle [50]. PPG signals are advantageous over ECG signals as they do not require complex hardware for their collection, do not need a reference signal and are more accessible as the "PPG sensors can be incorporated into wristbands" [50]. The HRV is further processed to extract frequency and time domain features [51], some of which are described in the Table 3.

Metric	Description	Domain
LF	Low Frequency: The "total spectral power of all NN intervals with frequency ranging from 0.04 Hz to 0.15 Hz" [51]	Frequency
HF	High Frequency: The "total spectral power of all NN intervals with frequency ranging from 0.15 Hz to 0.4 Hz" [51]	Frequency
LF/HF	Ratio of LF to HF power	Frequency
SDNN	"Standard deviation of all NN intervals" [51]	Time
SDANN	"Standard deviation of the average NN intervals" [51]	Time
RMSSD	"Square root of the mean squared differences of successive RR intervals" [51]	Time
pNN50	"Percentage differences of successive RR intervals larger than 50 ms" [51]	Time

Table 3: HRV features in time and frequency domain. NN denotes interval of time between two heartbeats. Adapted and modified on the information from Table 1 of [51].

How are emotions investigated?

Emotions are modelled using either of the following two theoretical approaches: The Basic Emotions Approach or The Dimensional Approach [52]. The basic emotions approach professes that humans possess a "discrete and limited set of basic emotions"; and each emotion "arises from activation within unique neural pathways of the central nervous system CNS", thus, differing from other emotions in psychological, physiological, and behavioural manifestations [31]. However, this approach has been criticised due to insufficient empirical evidence [31].

The dimensional approach distinguishes emotions based on two or three dimensions [52]. The two-dimensional model ("The Circumplex Model of Affect") has been described above, with "valence" and "arousal" as the independent dimensions. As a modification to the valence-arousal model, the three-dimensional model introduces the dimension of "dominance" which ranges from weak to strong; and is referred to as PAD (Pleasure-Arousal-Dominance) model [53]. An example of this is the Self-Assessment Manikin (SAM) [54], which consists of "a set of three pictorial assessment scales that measure the pleasure, arousal, and dominance associated with a person's affective state" [21].

How is mood investigated?

Mood is measured using either of the implicit or the explicit approach [30]. The explicit approach focuses on self-report questionnaires, whereas the implicit approach interprets the mood automatically on the basis of physiological and behavioural signals captured from an individual [30]. A drawback of the explicit approach is that it is not applicable for continuous measurements as participants have to halt their activities to fill the self-report questionnaires [21]. Moreover, self-reported moods are prone to personal bias [21] and long item-based questionnaires are time-consuming and can be burdensome as they require cognitive reasoning [21]. The advantages of following implicit approach as mentioned by P. M. A. Desmet et al. [21], are that they "allow for continuous measurement in real-time", without disrupting the user's experience, i.e., having to stop their activities to report mood. Moreover, such measures are not biased by cognitive constraints.

While acknowledging the "explicit approach" [30] as "self-expression", where individuals self-report their momentary mood states, Desmet [55], further investigated the "implicit approach" [30], and classified mood assessment technology into three categories, namely: wearable sensors, non-contact sensors, natural contact sensors.

1. Wearable sensors, also known as "affective wearables", such as the Hexoskin shirt, come in direct and continuous contact with a human body and collect physiological signals (respiratory rate, skin conductance, heart rate etc.) [55].
2. Non-contact sensing does not require a physical contact between a sensor device and a human body. Mood is assessed by interpreting behavioural, vocal, and/or visual signals such as posture, facial expressions, and muscular patterns [55].

3. Natural contact sensors, which also collect physiological signals, are embedded on to daily life objects that a user interacts with, such as on the steering wheel of a car, on a computer chair, or on a computer mouse [55].

According to Siegel et al. [56], variations in quantitative measurements of physiological (or "ANS" (autonomic nervous system)) signals are to be expected and should not be solely attributed to "variability in the experimental method", but instead should also account for the situational factors and context. Therefore, while collecting signals for mood detection using one or more of the implicit approaches discussed above, care should be taken to adjust the sensitivity of sensor devices (for ideal calibration of sampling rates) and accommodate for the specificity (such as heterogeneity among individuals as well as across cultures).

What is affective computing?

Affective computing is an interdisciplinary field of study encompassing neuroscience, psychology, engineering, education and computer science [57], which aims to develop computational systems that perceive and respond to the affective states (emotions and moods) of an individual [58], for the purpose of improving the interaction between humans and computer-based systems [19]. Picard [59] divided affective computing into four categories based on the criteria of perception and expression of affect:

Category 1: Computers that can neither perceive affect nor express it.

Category 2: Computers that cannot perceive affect but can express affect (such computerized voices which mimic "natural intonation").

Category 3: Computers that can perceive affect but cannot express it.

Category 4: Computers that can both perceive and express affect.

Category 1 and 2 of computers can be discarded in creating affectual AAL solutions as they are incapable in identifying real-time affective experiences of the users [58]. Category 4 seems to be ideal for a complete personalized computing, nonetheless, category 3 is equally crucial to enhance AAL technologies, as it would allow for the computerized algorithms to acknowledge the affectual context before recommending/responding with a solution.

Why is mood suited better for affective computing?

The decision to study any construct of affect (emotion or mood) lies in the research goals of the study. Since, the target population of AAL solutions are older adults (65+), we decided to specifically focus on studying their mood because of the following reasons:

1. Moods exist for longer periods of time (hours to days), as compared to emotions that exist for a very short span of time (seconds to minutes). Therefore, it is possible for older adults to be cognitively aware of their mood(s) at any given point of time in a day, whereas conscious awareness of each and every emotion experienced in natural contexts is not feasible. Even if it was feasible, it would still have been mentally and physically exhausting to report multiple emotions and their respective stimuli multiple times a day, whereas a limited number of moods could be practically reported in a single day.
2. Emotions are reactions to a specific stimuli and they are often induced using artificial provocations in controlled lab environments [60]. However, the induced reaction might not be similar to a natural reaction, thus resulting in inaccurately trained models for practical (real-life) deployment, whereas moods occur in natural contexts and are "a response to cumulative causes". Therefore, affect recognition systems based on mood(s) would be more robust and practically deployable.

The "In-The-Wild" Methodology

F. Larradet et al. [60], argued that the physiological signals used to detect affective states, are purposefully induced in lab conditions i.e., at a specific time, with a pre-determined stimuli and with limited contextual factors from the environment. This approach is inadequate because of the following two reasons:

1. Induction of the desired response in participants is uncertain, even if the experimental procedure is highly controlled, as "people can react differently to the same stimuli" [60]. For example, some people tend to enjoy horror movies while some might find them scary [60].
2. Physiological signals vary with the fitness level of a person and their age [60]. Periodic retraining of affect recognition models would be tedious if "in-the-lab data" needs to be collected every time [60].

Hence, the recognition models built upon 'induced-physiological signals' would not be efficiently applicable in real-life scenarios (such as in Ambient Assisted Living).

As a solution to the limitations mentioned above, the "In-The-Wild" methodologies are proposed, which abstain the researchers from controlling the experimental variables, and participants are monitored in real-life scenarios, thus, enabling collection of signals in natural context [60]. This also saves the experimental effort to prepare experimental conditions and a dataset of the required stimuli, which would otherwise have been repeatedly required due to fluctuations in physiological signals according to age and fitness [60]. Moreover, the in-the-wild methodologies are advantageous as they are not limited by ethical constraints; as research ethics boards only allow for low intensity negative stimuli to be used in research studies, whereas real-life scenarios are not restricted and can have high levels of intensity, irrespective of valence [60].

The "affect-related events" however require to be annotated/labelled, even when captured in-the-wild [60]. Two approaches have been discussed for this purpose:

1. Expert labelling [60]: A single, or a group of specialists observe an individual's behavioural (facial, postural) or physiological signals, and annotate them using their expertise. This approach suffers from drawbacks such as disagreement among experts [60], difficulty in synchronizing signals capture in-the-wild using multiple modalities[60]. Moreover, being monitored by other humans might feel as intrusion of privacy to the participants.

2. Self-reporting [60]: The concept of self-reporting has already been explained above while discussing the implicit approach to report mood, where an individual reports their affective experiences, the intensity of those experiences and the context in which they were experienced. Apart from the shortcomings of self-report measures mentioned above, some more were highlighted in [60]: failing to understand gender- or culture-specific terminology, reporting irregularly or forgetting to report at all, and underrating the intensity of their experiences (particularly if they are negative).

A drawback of in-the-wild studies mentioned by [60] was that the annotated signals might lack additional contextual information of the reporting environment, which could otherwise (i.e., in lab experiments) be known and in full control of the researcher. E.g., unreported factors such as consuming coffee, drug-intake, or alcohol use, which are known to influence physiological indicators, could result in corrupted labels [60]. Moreover, participant mobility could introduce noise in the signals, and needs to be accommodated for (by multiple layers of processing), to develop truly ambulatory systems [60].

Implications for including mood measures from a computational perspective

Balters and Steinert [61], while proposing to use the dimensional theory for affect based engineering (i.e., affective computing), accentuated on the research gap that "it is not yet possible to precisely and reliably detect and quantify the valence level corresponding to a specific arousal value". E.g., extremely happy and extremely angry have the same arousal and can be only differentiated by their valence [61]. Consequently, the authors [61] emphasized on the need for a tool to register complementary data inputs to record valence.

From the literature discussed in the previous sections, it can be inferred that, irrespective of the approach (implicit or explicit) being followed to capture mood, self-report instruments are vital for the field of affective computing. Such instruments can be the ideal complementary tools in affective computing, as they are reliable, easy to use, and can measure distinct mood types [21], and are free from the drawbacks of expert labelling such as intrusion of privacy, cost of hiring experts, and disagreement amongst the annotators. Particularly, the implicit approach which focuses on automatic recognition of affect, can benefit from real-time annotation of signals leading to finest precision in computation, and help in detecting patterns of certain behaviours, such as episodes of mood disorders.

Selecting self-report measures

Ekkekakis and Russel [37], warned against the widespread errors of selecting self-report measures for "research dealing with affect, mood, and emotion", some of which are:

1. Selecting a measure without providing a concrete rationale, often justifying the selection of a measure only because it has been used commonly in previous scholarly works.
2. Combining multiple measures without accounting for their complementary effects on each other. This has also been emphasized by Desmet et al. [21], who stated that instruments which measure emotions are "not necessarily equally suitable for measuring mood" [21].
3. Using measures which were not originally developed for the domain of affect being studied in the research.

Therefore, the authors [37] advised to carefully select the self-report instruments for a given construct, optimally supported with theoretical and psychometric rationale. Moreover, Brown and Astell [38], identified key issues in existing mood assessment techniques, which were: "the number of items used to assess each mood construct", the temporal perspective adopted by the users, and "the pervasiveness of self-report measures". It was also stated that self-report methods are vulnerable to individual differences and the assessment technique should be carefully selected (with high reliability and validity) for the population of interest. Similarly, Lucas [39], with a focus on selecting self-report measures for subjective-wellbeing, recommended choosing the measures with "desirable psychometric properties", which are high levels of reliability, convergent, discriminant and construct validity. These are elaborated as follows:

- High levels of reliability, which "assess the extent to which measures are free from measurement error", and can be defined using quantitative indices [39].

- High levels of validity. Validity is defined as “whether a test measures what it is supposed to measure” [39], and can further be split into:

    - Content validity: “Refers to the extent to which the measure in question captures the breadth of the construct of interest, without including content that should theoretically be excluded” [39].
    - Convergent and discriminant validity: “Complementary forms of validity that reflect the extent to which a measure correlates strongly with other related measures (convergent validity) and correlates weakly or not at all with measures to which it should be unrelated (discriminant validity)” [39].
    - Construct validity: “Reflects the extent to which a measure behaves as it would be expected to behave, given theories about the construct itself. Thus, to test construct validity, one must have some idea about how a measure should relate to additional constructs” [39].

To prevent point 2 and 3 in the widespread errors discussed above, only mood specific questionnaires were selected for this study. Although, verbal self-report measures are capable of capturing distinct mood types, they cause cognitive loading and are generally time-consuming [21]. Moreover, Davies et al. [62], argued that verbal measures require a certain degree of literacy to be comprehended by participants, whereas pictorial scales are intuitive, accurate, and quick [21]. Therefore, both verbal and pictorial measures were chosen to be evaluated.

Need for a user-centred approach in selecting self-report measures for mood

As older adults will lead the adoption of technologically-enhanced healthcare solutions, it is important to integrate their opinions in the design process and to “empower them to influence ongoing developments according to their personal needs” [63]. User-centred design (UCD) is defined as “an approach that involves end-users throughout the development process so that technology support tasks, are easy to operate, and are of value to users" [64]. Following a user-centred design will help us in determining which self-report measures are cognitively and physically exhausting and should be avoided in affective research in a population with diminishing capacities. As compared to human-centred design (HCD), UCD is more specific towards the target population (older adults in this case), and is thus better suited for this study. Moreover, the iterative nature of user-centred design will ensure future refinement and validation of the prototype(s) derived from this initial study, and is therefore, better than the methodologies that solely rely on designing end products (tools and technologies) based on responses from a single survey questionnaire.

Need for real-time assessment of mood

Conventionally, the affective (hedonic) components of subjective well-being were captured retrospectively [39], such as asking the respondents to report their moods in the previous week or the past month [40], along with the intensity and frequency of those affective experiences [39]. However, with the passage of time, people tend to rely on their "semantic knowledge" of how one would typically feel in a given situation, rather than relying on the "episodic memory of the actual experience" [39]. The aggregation of affective experiences over long time is influenced by certain biases (such as the recall bias), which lead to inaccurate reconstruction of the actual affective experiences [39], and according to Steptoe et al. [40], an evaluative response is induced instead of a hedonic response when measured in retrospect.

To overcome this problem, affective experiences should be recorded in real-time using Ecological Momentary Assessment (EMA) technique, which could be either signal-dependent (i.e., respondents reporting their mood in response to a signal such as a notification or an alarm) or event-dependent (i.e., respondents reporting their mood after a predetermined event such as before breakfast every day) [65].

Self-report instruments selected

Verbal self-report instruments are capable of capturing distinct mood types, but are cognitively taxing and time-consuming [21]. Pictorial scales, on the other hand, are intuitive, accurate, and quick [21]. Therefore, both verbal and pictorial instruments were chosen to be evaluated in this study. To keep the time limit of a semi-structured interview within an hour, 1 verbal (adjective-based) self-report measure and 2 pictorial measures (each differing in the type of interaction with the user) were chosen. As discussed thoroughly above on how to select self-report measures, we should avoid choosing an instrument just because of its widespread use, and rather select the measures with "desirable psychometric properties" [39] and concrete theoretical rationale [37]. The justification for choosing the self-report measures in this research is as follows:

Justification for choosing the Profile of Mood States 2 (POMS 2)

The POMS 2-Adult Short is a 35-item questionnaire and is provided by the Multi-Health Systems Inc. (MHS), (link: https://storefront.mhs.com/collections/poms-2 to obtain a copy of the instrument form the publisher). In this research (Chapter IV), POMS 2 Adult Short was administered locally with the purpose of assessment selected as "Test Run or Training" and the time frame selected as "RIGHT NOW" on the MHS website. This questionnaire represented the class of adjective (or verbal) measures of self-report, where each adjective was rated on a 5-Point Likert scale. We are unable to publish the POMS 2-S A, due to copyright issues.

As reviewed by Spielberger [66], the Profile Of Mood States (POMS) was originally developed for psychiatric patients to measure their fluctuating affective states. The POMS consisted of 65 items (adjectives), which described feelings or moods, and each mood was rated on a five-point scale to measure the intensity. Upon performing factor analysis, six different mood dimensions (each having 7 to 15 adjectives) were identified: "confusion-bewilderment", "depression-rejection", "tension-anxiety", "fatigue-inertia", "vigor-activity", and "anger-hostility". Each mood dimension had a mood score, which was calculated as the sum of reported ratings of all corresponding adjectives to that dimension.

Gibson [67] indicated that the dimensions of confusion, fatigue and vigor may be particularly important for older adults due to their frailty and lack of activation; and measured the validity and reliability of the POMS questionnaire, by administering it to 479 healthy and cognitively intact community dwelling older adults, to measure its validity and reliability. Upon performing principal components factor analysis on the responses, the author concluded that original factors from POMS were in very strong concordance with those identified in this study, with only 6 (out of 65) adjectives loading onto different factors. Moreover, excellent internal item consistency of the subscales was observed, with each adjective (item) contributing towards the reliability of total score on respective mood dimension (or subscale). Also, moderate to high test-retest reliability was reported and concurrent validity (against other validated mood state measures) was established. Discriminative properties of POMS were observed when the mean raw scores (of healthy older adults) were compared with those obtained from outpatients of a chronic pain management (who exhibited higher levels of negative mood than healthy older adults).

As stated by Spielberger [66], the Profile Of Mood States (POMS) was originally developed for psychiatric patients to measure their fluctuating affective states. Lin et al. [68], reviewed the Profile of Mood States 2nd Edition (POMS 2) which was published in 2012 to "assess transient feelings and mood among individuals aged 13 years and above". Apart from the original six subscales, the POMS 2 comprises of a "Friendliness" and a summary scale called the "Total Mood Disturbance (TMD)". Also, other revisions were done to the original POMS, such as addition of more positive mood states, deletion of culturally specific items and modernization of outdated adjectives. The intensity of mood is calculated on a five-point scale and the scales are scored online. Four versions for the POMS 2 were published, namely: POMS 2-Adult with 65 items, POMS 2-Adult Short with 35 items, POMS 2-Youth with 60 items and POMS 2-Youth Short with 35 items. Based on Cronbach's alpha coefficients, the authors reported that the items (adjectives) corresponded with each other and the test as a whole; and the test-retest reliability was reported to be moderately consistent for a period of one week. Good discriminant validity in the adult versions was observed when compared with a clinical group, and generalizability across ethnic groups was established. Confirmatory factor analysis resulted in data being "adequately fitted to the hierarchical model for the

POMS 2-A" and convergent validity was examined by comparing the correlation between scores of POMS 2 and PANAS-X, but reported only for POMS 2-A.

Based on the above mentioned psychometric properties (of good validity and reliability) for the adult version, and due to the drawbacks of long-item measures such as being time-consuming and burdensome [21], we selected POMS 2-A Short for our research with older adults.

Justification for choosing the pictorial scale: Pick-A-Mood

P. M. A. Desmet et al. [21], proposed a character-based pictorial scale to measure mood called "Pick-A-Mood". Based on the valence-arousal model, the authors created four mood categories, one for each quadrant (i.e., the "energized-pleasant" quadrant, the "calm-unpleasant" quadrant, the "energized-unpleasant" quadrant, and the "calm-pleasant" quadrant); and included 2 distinct mood expressions for each of the category. The choice to include only 2 moods per quadrant was to keep the scale simple, balanced [69] and the administration time short. The scale is represented by any of three sets of cartoons: a female, a male, or a robot. Each set contains 8 distinct mood expressions, namely: tense, irritated, calm, relaxed, bored, sad, cheerful, and excited. The original characters were obtained from the authors [21] under the creative commons license. Figure 5, modified on the information in [21] and characters obtained from the original authors, depicts the dimensional expansion of the Pick-A-Mood scale, for the male character. Permission for modification was obtained from original authors.

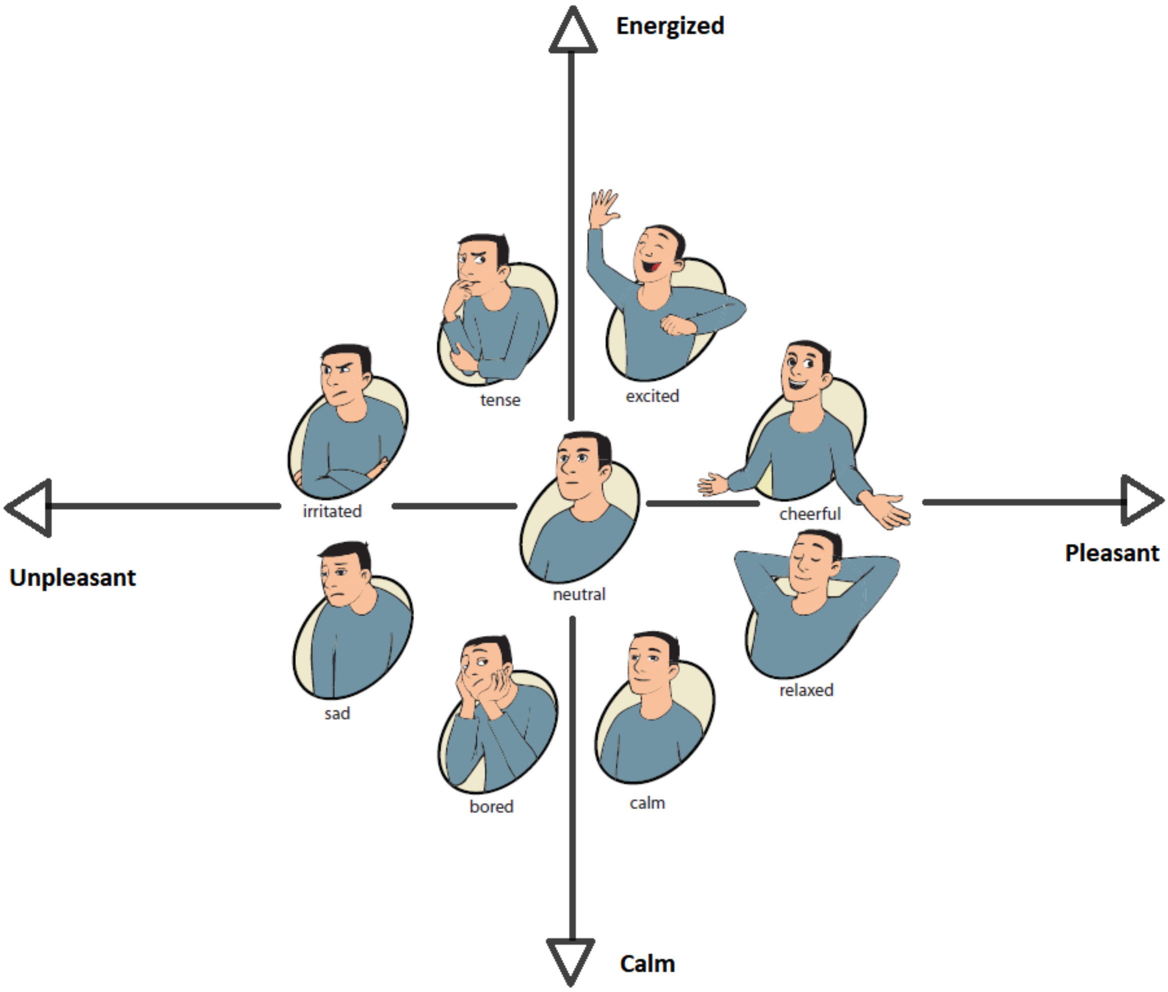

Figure 5: Valence (X axis) – arousal (Y axis) plane drawn around the original cartoons obtained from authors of “Pick-A-Mood” [21]. Eight distinct mood expressions (+ 1 neutral as the scale mid-point), two in each of the four quadrants of the valence-arousal plane, depicted for the male cartoon.

For the purpose of this study, a 5-point Likert scale was attached with the characters of Pick-A-Mood to measure the intensity of participants’ mood (ranging from “Not at all”: 1, “A little”: 2, “Moderately”: 3, “Quite a bit”: 4, and “Extremely”: 5). Figure 6 depicts the male version of Pick-A-Mood that was used in the research. The female version and the robot version (as a gender-neutral option) are attached in the appendix C.

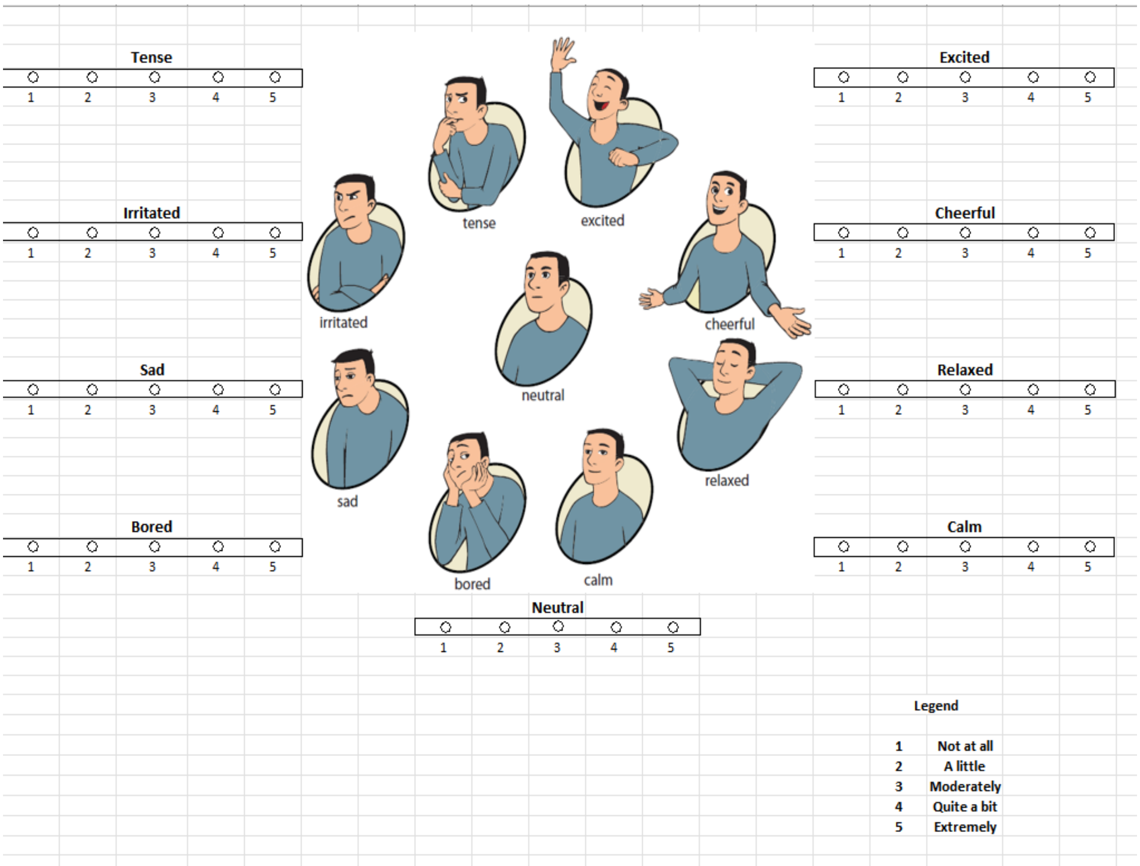

Figure 6: Modified version of Pick-A-Mood [21] with a 5-point Likert scale, for male cartoon.

These cartoons were produced by a professional cartoonist in several iterations to depict non-human characters analogous to human anatomy, i.e., neutral-aged female, and a neutral-aged male. The cartoons were validated through an evaluation study involving 191 participants from 31 countries, and aged between 13 and 76 years of age [69]. The evaluation study consisted of three stages: 1) To generate labels (text) for the expressions, 2) To select a text-label from a set of predefined labels for every expression, and 3) Rating valence and arousal of each expression on a five-point scale [69]. Upon performing statistical tests on the results of the evaluation study, the authors concluded that all of the four of the basic mood categories were represented via the cartoons, and the mood expressions within each category were represented with different valence and/or arousal values, thus adding distinction in each quadrant [69]. Moreover, the authors did not observe any significant gender effect [21].

Even though the evaluation study was not specifically done with older adults (participants aged between 13 to 76 years of age [69]), since this measure was theoretically supported, was tested across multiple cultures and different genders, and exhibited inter- and intra-category distinctions among different mood expressions, we chose to include this into our study as well.

Justification for choosing the pictorial scale: Visual Analogue Mood Scales – Revised (VAMS-R)

The revised version of Visual Analogue Mood Scales (VAMS-R) [70] was selected as the second pictorial scale. Nyenhuis et al., [71] described that the Visual Analogue Mood Scales (VAMS) [72] consist of nine cartoon faces, eight of which depict distinct moods namely: "energetic", "happy", "tense", "confused", "angry", "tired", "afraid", and "sad". The ninth face depicts a "neutral" mood. Each of the eight distinct mood faces is used to create a distinct mood scale, with the neutral face on top and the individual mood face at the bottom, separated by 100-mm vertical line. "The scales are presented in a vertical orientation to overcome invalid responses due to hemianopia and inattention" [70]. To improve the understanding of the scales, each individual mood face is also accompanied by a one-word verbal description below the cartoon, whereas for the neutral mood, the word "Neutral" is written on the top of the cartoon. In each of the 8 scales, the participants mark the 100mm line at a point which best describes how they feel on that particular day. Mood disturbance in each scale is calculated by measuring the distance in mm from the neutral mood i.e., neutral is interpreted as the starting point. A composite score is also calculated by summing all the scores, while reversing the scores of positive valence items (i.e., energetic, and happy).

Kontou et al., [70] in 2012 produced a revised version of the Visual Analogue Mood Scale (VAMS-R), and measured its psychometric properties in 50 healthy older adults and 71 aphasic stroke patients. Contrary to the original VAMS, where "Neutral" is always placed on the top of the subscale, the revised version (VAMS-R) places "Neutral" on top of the negative mood states (tense, confused, angry, tired, afraid, and sad) but reverses the polarity in positive mood states, i.e., "Neutral" is placed on the bottom and "Happy" and "Energetic" are placed on the top. This was done to improve the internal consistency of the scale , as it was observed in a study by [73], that both healthy older adults and stroke patients, failed to notice the polarity of the subscales in original VAMS [70]. Also, the internal consistency was reported to drastically improve (from $\alpha = 0.45$ to $\alpha = 0.73$) on removal of "happy" and "energetic" [73] [70]. The authors found the internal consistency of VAMS-R in healthy older adults at Cronbach's alpha coefficient $\alpha = 0.74$, with item-total correlations ranging from 0.26 to 0.58. Also, for healthy older adults, VAMS-R was found to be moderately correlated with the all scores of Hospital Anxiety and Depression Scale. Therefore, VAMS-R was chosen instead of VAMS in this study.

A drawback we noticed in this scale was that the original cartoons were not very informative in expressing the moods (specifically for the "energetic" mood). As pictorial scales should be intuitive, accurate, and quick [21], we decided to modify the cartoons for VAMS-R. Moreover, to make the scale interactive in a digital format, a 0-100 touch slider for each subscale (total of 8) was added. Although, we are unable to publish the VAMS-R scales used in this research due to copyright permissions on the cartoons (emojis) used for construction of the scales, Table 4 provides the Unicode for the respective emojis used. As per [70], the polarity of neutral was reversed for positive moods (energetic and happy). Also, the subscales were administered individually, in a total of 8 iterations (one for each mood).

Expression depicted	**Unicode for respective emoji**
Neutral	U+1F610
Afraid	U+1F628
Angry	U+1F620
Confused	U+1F914
Tired	U+1F971
Happy	U+1F642
Sad	U+2639
Tense	U+1F61F
Energetic	"Mascot Smiley Basketball Illustration" [74] (Obtained under Adobe Stock Standard License)

Table 4: Source or Unicode for respective emojis used to construct VAMS-R

Research Aim

This thesis aimed to investigate the acceptability and feasibility of including self-report instruments of mood change in the research and development of AAL solutions, so that the affective experiences collected from the daily lives of older adults (using objective and/or subjective measures) can be leveraged to enhance the context-awareness of assistive technologies, thus, leading to appropriate and personalized care.

Research objectives

This research has been divided into two main parts: one quantitative and one qualitative.

1. The quantitative part of the research (Chapter III) explores the first research question:

    RQ1. To investigate whether biological signals captured from minimally intrusive wearable sensors can be used to detect human affective experiences?

2. The qualitative part (Chapter IV) consists of an interview study with the residents of a long-term care facility, to investigate the following research questions:

    RQ2: To find out which self-report measure of mood is preferred by older adults and why?

    RQ3: How frequently would the older adults feel comfortable in reporting their moods daily?

    RQ4: Which format (electronic or paper-based) would older adults prefer to self-report?

Note: It is important to clarify at this stage that the terms 'affect', 'affective states' and 'affective phenomenon' used in the Chapter III consist of both 'emotion' and 'mood'. A distinction could not be made as the exploratory data analysis is done on a secondary dataset. In Chapter IV, 'mood' has been studied distinctively.

Chapter III: Quantitative Study

Introduction to PATH

The Program to Accelerate Technologies for Homecare (PATH, https://pathplatform.ca/), in collaboration with the industry partner SmartONE solutions (https://smart-one.ca/) and four academic institutions (University of Ottawa, University of Toronto, University of Alberta and University of Waterloo), aims to provide "a network that creates a pathway for rapid testing and commercialization of new home health products". To contribute towards this project, the team at Ottawa received a bundle of 5 home automation products namely Fitbit Aria (weighing scale), Withings Sleep (sleep tracker), AWS DeepLens (deep learning enabled video camera), Empatica E4 wristband and Hexoskin pro kit (shirt and sensor). Also, the University of Ottawa partnered with Perley Health (https://www.perleyhealth.ca/), which is a local seniors' healthcare centre that promotes research and clinical innovation.

Out of the devices received, the Empatica E4 wristband, the Hexoskin shirt and AWS DeepLens were initially selected as good candidates that aligned with my research to capture and study the daily mood(s) of older adults using sensor modalities. Through dialogue with Perley Health, the notion to include AWS DeepLens (to study facial expressions) was rejected, as continuous video monitoring could have resulted in invasion of privacy. Moreover, as discussed in the literature, the use of physiological modalities to detect affect is more advantageous over behavioural modalities (such as facial expressions). To test the functioning of qualified wearable devices (E4 wristband and Hexoskin shirt), I conducted a pilot study with two graduate students. Although the devices were functioning properly in terms of physiological signal collection, some barriers in collecting data from older participants were unearthed upon discussion with the director of researcher operations at Perley Health, such as the burden of the sensor devices on the frail population (weight and comfort of the device, and length of the time wearing them).

As reviewed in the literature, moods exist for long periods of time (spanning across hours, or even days), have a gradual onset and a low intensity. Therefore, detecting mood(s), particularly by using the "in-the-wild" methodology, would have required long-term continuous collection of physiological signals, implying a prolonged period of wearing the devices. The Hexoskin shirts, which are recommended to have a snug fit against the body [75] (for proper skin to sensor contact), and to be used with a conductive gel to accurately record the electrical activity [76], would have generated discomfort and hygiene issues for older adults in a longitudinal study requiring prolonged periods of wearing. Therefore, only the Empatica E4 wristband was selected to monitor the real-time physiological signals, as it is lightweight and minimally intrusive.

Figure 7: Empatica E4 wristband.

The Empatica E4 (https://www.empatica.com/research/e4/) wristband (depicted in Figure 7) is equipped with four sensors namely: three-axis accelerometer which captures motion based activity, infrared thermopile to read the skin temperature, a photoplethysmography (PPG) sensor which measures the blood volume pulse from which heart rate variability is extracted, and an electrodermal activity (EDA) sensor to measure the fluctuations in the electrical properties of the skin. The data from each recording sessions is stored in a .zip archive which contains 7 files, out of which the raw data files i.e., Electrodermal Activity (EDA), Temperature (TEMP), Blood Volume Pulse (BVP or PPG) and Acceleration (ACC) are present in a .csv format. The starting time of a recording session (as Unix time stamp in UTC format) is stored in the first row of each of these files, and the second row contains the sampling rate of respective signals (as depicted in Table 5).

Signals collected from Empatica E4	Sampling Rate (in Hertz)	Measurement Units
Acceleration (ACC), in x, y, and z axis	32 Hz, in each axis	1/64 g
Electrodermal Activity (EDA)	4 Hz	micro siemens (µS)
Temperature	4 Hz	Celsius (°C)
Blood Volume Pulse (BVP or PPG)	64 Hz	Not provided

Table 5: Different signals recorded by the Empatica E4 watch, along with their measurement units and sampling rates.

Before formulating and conducting experiment(s) with older adults, it was necessary to collect evidence on the usability of E4 wristband for affect detection. To accomplish this task, and to answer the first research questions (i.e., to investigate whether biological signals captured from minimally intrusive wearable sensors can be used to detect human affective experiences?), exploratory data analysis was performed on a publicly available dataset for stress and affect detection, collected and published by P. Schmidt et al. [77] in 2018.

Description of the WESAD dataset [77]

Schmidt et al. [77] in 2018, published a multimodal dataset for Wearable Stress and Affect Detection (abbreviated as WESAD), consisting of “all physiological modalities commonly integrated in commercial and medical devices”, including “blood volume pulse (BVP), electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG), respiration (RESP), body temperature (TEMP), and three axis acceleration (ACC)”. This dataset was collected with 15 participants (12 male, 3 female) in the mean age range of 27.5 ± 2.4 years, using two wearable devices: the 'RespiBAN Professional' (placed around the chest) and the 'Empatica E4' (worn on the non-dominant hand). The data was labelled from S2 to S17 (indicating each subject), with S1 and S12 missing due to malfunctioning of sensors. The study protocol followed two different versions (A and B, described in the Table 6), with the goal to induce three different affective states (neutral, amusement and stress) in the participants, with two sessions of guided meditation in between to "de-excite" the participants post stress and post amusement.

Version A	**Version B**
Baseline	Baseline
Self-report	Self-report
Amusement	Stress
Self-report	Self-report
Meditation 1	Rest
Self-report	Meditation 1
Stress	Self-report
Self-report	Amusement
Rest	Self-report
Meditation 2	Meditation 2
Self-report	Self-report

Table 6: Different version of the study protocol [77] used to create the WESAD dataset.

To induce a neutral affective state, a 20-minute baseline after wearing the sensors was recorded, with the subjects reading neutral magazines while sitting or standing. The amusement condition was induced by making the subjects watch 11 "funny video clips". To induce stress, the researchers employed the Trier Social Stress Test (TSST), which required the participants to complete a public speaking and then an arithmetic task. This condition was followed by a ten-minute rest period. Also, two guided mediation session were conducted to de-excite the participants from amusement and stress. In between the affect inducing conditions, the subjects were asked to fill out multiple self-report questionnaires (mentioned as Self-report in Table 6).

Methodology

From the complete WESAD dataset available, only the E4 data was of interest (as this device aligns with our research goals of being minimally intrusive and less burdensome), so the "RespiBAN Professional" dataset was rejected. Moreover, for the analysis, only the raw E4 data provided for each participant was used (specifically the physiological signals of temperature (TEMP), electrodermal activity (EDA) and the blood volume pulse (BVP)). Apart from the sensor data, the authors supplied a "quest.csv" file for every participant, which included the specific timings for different protocol conditions from the start of respective experiments, as well as the responses of the participants to different self-report questionnaires. The authors had suggested using either study protocol conditions as labels or the answers to the self-report questionnaires as labels, to which the former was chosen.

I also made a few assumptions for my analysis. I treated the period after the baseline condition and before the first activity as "neutral". Secondly, I renamed each of the mediation periods as a "relaxing activity". Also, I was interested in analysing how body reacts after going through stress, and included this period in my analysis as well.

The exploratory data analysis was done on a personal computer with a 64-bit Windows 10 operating system, powered by AMD Ryzen 5 4600H processor, equipped with 16GB ram, and by using Python 3.8.6 and the following general Python libraries: NumPy 1.19.3, Pandas 1.1.3, matplotlib 3.3.2 and seaborn 0.11.1. Some specific libraries published to analyse E4 data were also used namely, the "FLIRT: A feature generation toolkit for wearable data" [78] and the "NeuroKit2: A Python toolbox for neurophysiological signal processing" [79].

Specifically, the FLIRT package was used to read the raw E4 files, which converted them into pandas dataframe with two columns, "datetime" and the respective signal (either of temperature, electrodermal activity or blood volume pulse). As the sampling frequency of both the temperature and EDA were 4Hz (i.e., 4 seconds in one second), I decided to combine them into a single dataframe, whereas the BVP signal, sampled at 64Hz was kept in a separate dataframe. Moreover, instead of using the absolute date and time of the experiment (which were different for each participant), I added a relative time column to each of the dataframe, which started at 0 for each participant, and fragmented 1 second into (1/Sampling_Frequency) parts respective to the signal (e.g., for a 4Hz signals, 1 second was fragmented into of 4 parts, i.e., 0.25, 0.5, 0.75 and 1). This provided a consistent frame of reference for visualizing and comparing the physiological signals of different participants.

The study protocol conditions were read from the "quest.csv" for each participant into a Python dictionary (depicted for S10 in the Figure 8), with the protocol condition as the key and their start and end time (in seconds) as values. Apart from the original conditions (Base, TSST (for Stress), Fun, Medi 1 and Medi 2), I added two more (Neutral and Post_Stress) conditions into the dictionary data structure, as discussed in the assumptions.

```
Subject: S10
{'Base': [125, 1325], 'Neutral': [1326, 1672], 'Fun': [1673,
2065], 'Medi 1': [2322, 2704], 'TSST': [3243, 4015],
'Post_Stress': [4016, 4996], 'Medi 2': [4997, 5415]}
```

Figure 8: Protocol conditions with respective times (in seconds) for S10.

It can be noted that the time for baseline starts from 125 seconds for the subject S10. This is due to the reason that the authors started counting the time when the RespiBAN device started recording the signals, and labelled the conditions accordingly. According to my understanding, the 125 second mark signifies the time when both E4 and RespiBAN devices were manually synchronized by the authors (discussed in the readme file of the dataset [77]). To maintain the readability of this document, only the results of analysis performed on subject 10's (S10) data will be discussed in this section, and the relevant material for other subjects will be attached in Appendix B.

Electrodermal Activity (EDA) and Temperature Analysis

After pre-processing the signals and saving the protocol conditions, I visualized the electrodermal activity for each participant by plotting a time-series graph, where the x-axis was occupied by the relative time in minutes (discussed above), the y-axis by electrodermal activity in micro-Siemens and the respective protocol conditions in coloured rectangles. This can be seen in the Figure 9. According to my assumptions, the mediation activities (Medi 1 and Medi 2) were combined as “relaxing activity” in the visualizations. To enhance the accessibility of this thesis, an inbuilt colourblind-safe colour palette from the seaborn library in Python was chosen for visualizing the data. Specifically, the following colour scheme (in hex codes) was used: The EDA signal: '#0173b2', Baseline: '#cc78bc', Amusing Activity: '#ece133', Relaxing Activity: '#029e73', Stressful Activity: '#ca9161'.

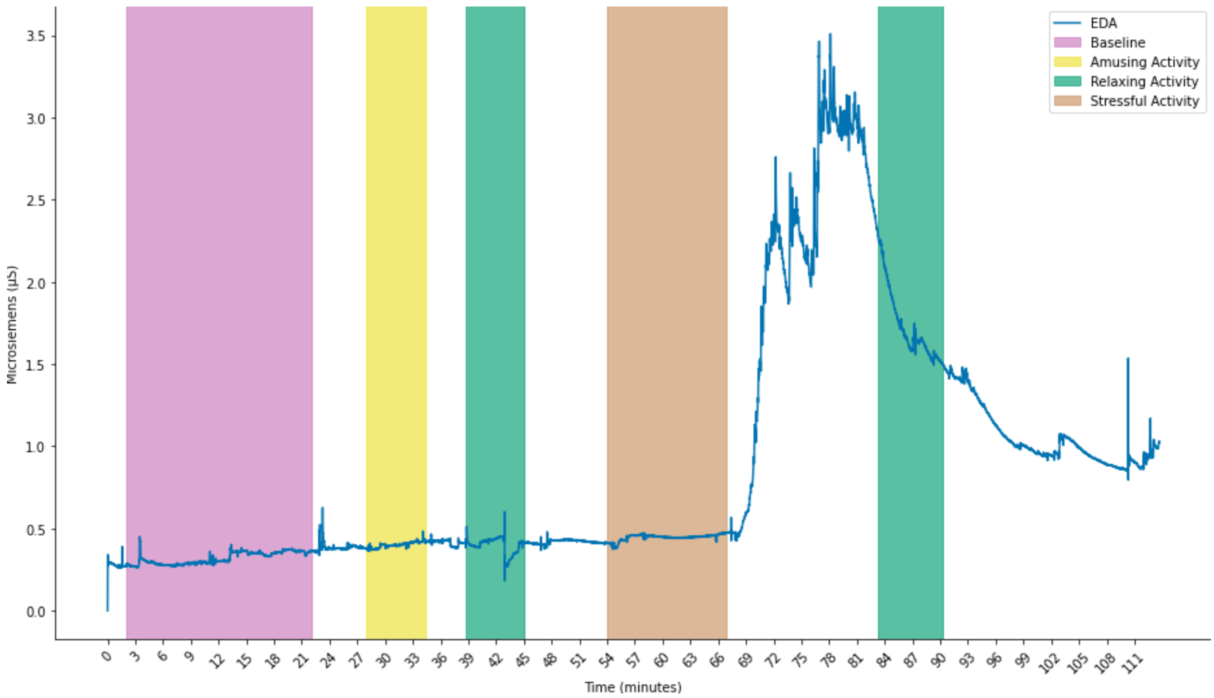

Figure 9: Visualization of electrodermal activity for S10, with coloured rectangles as protocol conditions.

The following statistical features were calculated and extracted from the EDA and temperature signals: 'eda_mean', 'eda_std', 'eda_min', 'eda_max', 'temp_mean', 'temp_std', 'temp_min', 'temp_max'. This has been displayed in Table 7 for subject 10. Baseline condition was ignored as it was utilized only to bring participants to a neutral affect. Instead, Neutral condition was used, where each participant was in their neutral state.

Features	Neutral	Stressful Activity	Post Stress	Meditation 1	Amusing Activity	Meditation 2
eda_mean	0.382884423	0.446193128	2.132589957	0.396349805	0.399660046	1.737692519
eda_std	0.020576325	0.01843341	0.867130818	0.04895368	0.017214574	0.212661245
eda_min	0.337039663	0.373124692	0.424864066	0.181845255	0.362802183	1.493804962
eda_max	0.626847245	0.475843082	3.509852909	0.602186428	0.483706374	2.281218844
temp_mean	33.32654874	34.38548721	34.01614639	34.09913015	33.61842575	32.9740526
temp_std	0.060871546	0.107986504	0.516256282	0.084054169	0.090469393	0.05489175
temp_min	33.16	34.21	33.09	33.99	33.41	32.89
temp_max	33.45	34.63	34.71	34.29	33.87	33.13

Table 7: Temperature and EDA features for S10.

Furthermore, as reviewed in the literature, I decomposed the electrodermal activity (using the NeuroKit2 [79] Python package) to investigate the phasic and tonic components of the signal. An example of this can be seen in Figure 10, where the phasic component of EDA is displayed in blue (hex code: '#0173b2') and the tonic component in orange (hex code: '#de8f05').

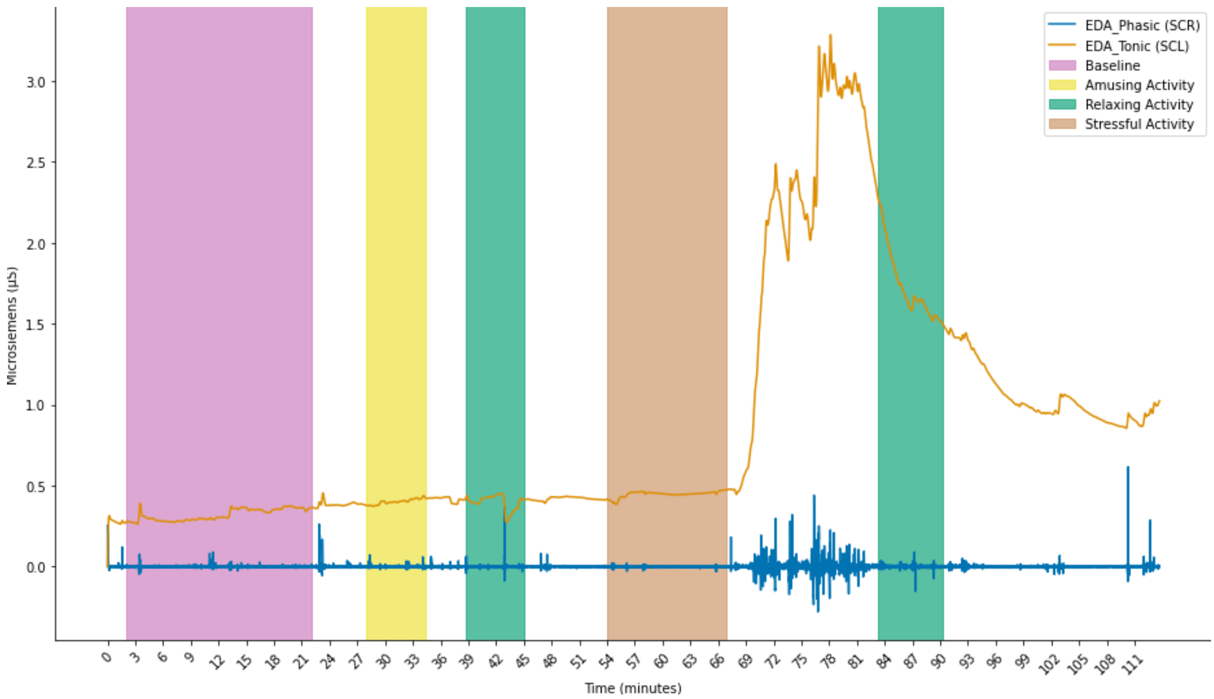

Figure 10: Electrodermal activity of S10 decomposed into phasic and tonic components.

The statistical features extracted from the tonic and phasic signals are depicted in Table 8 for subject 10.

Features	Neutral	Stressful Activity	Post Stress	Meditation 1	Amusing Activity	Meditation 2
tonic_mean	0.382890723	0.446193174	2.132580849	0.396346316	0.399681039	1.737707826
tonic_std	0.015133207	0.018046613	0.864740448	0.046721606	0.01662056	0.212479944
tonic_min	0.356964464	0.383608486	0.445095028	0.274632235	0.372256258	1.502881878
tonic_max	0.4533125	0.473928173	3.285470659	0.451452045	0.436631839	2.278822169
phasic_mean	-6.30E-06	-4.59E-08	9.11E-06	3.49E-06	-2.10E-05	-1.53E-05
phasic_std	0.012373096	0.003258073	0.049130198	0.01292109	0.004134222	0.008751175
phasic_min	- 0.059490106	-0.029031022	- 0.271240372	- 0.182404536	-0.02293809	- 0.104431695
phasic_max	0.184181612	0.020829529	0.435269804	0.22458244	0.050879973	0.077226566
Number of SCR peaks	3	0	49	2	0	2
SCR Peaks Mean Amplitude	0.165299879		0.137994158	0.139935146		0.119468337

Table 8: Phasic EDA and Tonic EDA features for S10.

Heart Rate Variability (HRV) Analysis using the Blood Volume Pulse (BVP)

The heart rate (BVP) data was very dense to be analysed visually given the fact that 64 samples were captured every second (64Hz sampling rate). Therefore, only statistical analysis could be performed on the features extracted from Heart Rate Variability, calculated using the NeuroKit2 [79] library. I also renamed the experiment conditions (i.e., dictionary keys from Figure 11), changing "Fun" to "Amused" and "TSST" to "Stressed".

```
S10
{'Base': [125, 1325], 'Neutral': [1326, 1672], 'Amused': [1673, 2065],
'Medi 1': [2322, 2704], 'Stressed': [3243, 4015], 'Post_Stress':
[4016, 4996], 'Medi 2': [4997, 5415]}
```

Figure 11: Renamed protocol conditions with respective times for S10.

A time segment of six minutes (360 seconds), before the end of each of the three affective states: neutral, amused and stressed, was chosen for feature extraction. E.g., In case of S10, the HRV features were extracted for Neutral state from 1312 to 1672 seconds, for Amused state from 1705 to 2065 seconds, and for Stressed state from 3655 to 4015 seconds. The HRV features (described in Chapter II, Table 3) along with their values are presented in Table 9 for S10, and in Appendix B for all participants.

Extracted_Features	S10_Neutral	S10_Amused	S10_Stressed
HRV_MeanNN	728.4286437	720.5070281	779.3180586
HRV_SDNN	374.0019399	480.0489454	140.2394176
HRV_SDANN1	118.9995917	109.1504186	32.14073738
HRV_RMSSD	413.5327865	632.5313335	161.3995189
HRV_pNN50	37.24696356	43.37349398	33.40563991
HRV_LF	0.006858283	0.030285378	0.037976317
HRV_HF	0.011092464	0.001719183	0.033275627
HRV_LFHF	0.61828314	17.61614406	1.141265266

Table 9: HRV features for S10.

Results after performing exploratory data analysis:

As discussed in the literature, everyone experiences affective phenomena differently even if the stimulus is same [60]. Similarly, P. Schmidt et al. [77] emphasized on the fact that each human perceives and reacts to affective stimulus differently, and care should be taken to train personalized machine learning models. Therefore, making comparisons between the features, extracted from affective data of different participants is not of much use. Instead, the features of every individual should be compared against their own baseline or different affective states. Some common patterns were observed by analysing the WESAD data collected from the E4 wristband, which are stated as follows:

1. Upon visually analysing the decomposed EDA plots for all participants (EDA plots attached in Appendix B), a pattern was observed where a radical increase in the tonic component (SCL) of the electrodermal activity was seen for all but two (S14 and S17) participants, in the time-period following the stressful activity. Therefore, in future studies, an increase in the slope of tonic EDA could be explored for its correlation with stress. Although statistical features such as the number of SCR peaks and mean SCR amplitude (Table 8) looked promising, a computational error ("ValueError" specifically) was encountered in case of subjects S2, S7, S8, S14, while extracting the peaks of phasic (SCR) component of the EDA signal via NeuroKit2 [79]. Consequently, no statistical comparisons were performed using the number of SCR peaks and the mean amplitude of SCR peaks from EDA signals in this study, and only visual comparisons were done to identify underlying patterns.

2. It was observed that 14 out of 15 participants had a higher LF/HF power ratio in either of stress or amused conditions as compared to the neutral condition (presented in Appendix B Table 43). This aligns with the literature [49], which states that low-frequency (LF) power spectrum corresponds to the contributions of sympathetic nervous system (SNS) such as response to stress or excitement, whereas high-frequency (HF) power spectrum corresponds to the contribution of parasympathetic nervous system (PNS) which is indicative of restful condition.

3. After comparing the mean values of temperature (displayed in Appendix B Table 45), 11 participants had highest mean temperature during or after stressful activity. In the same table, 10 participants are seen to have recorded their lowest mean temperature in relaxed states (either of Relaxed 1 (meditation 1) and Relaxed 2 (meditation 2).

4. No concrete pattern was observed on comparing mean EDA values (Appendix B Table 44), as highest and lowest values for each participants are distributed throughout the table.

Limitations and Drawbacks

1. The analysis in Chapter III was purely descriptive and not inferential. Therefore, no statistically significant inferences about a population can be made.

2. The number of affective states studied in the WESAD dataset is very limited and most of the affective states occur only once, as the experiments were conducted for a short span of time. Therefore, patterns between similar states, such as between multiple episodes of stress could not be determined.

3. The occurrence of computational errors (such as the "ValueError") during feature extraction questions the reliability of pre-built signal processing packages.

4. The participants in the WESAD study were required to fill multiple self-report questionnaires five times, as reported in Table 6. This cannot be replicated in a fragile population, such as the older adults, as it could lead to mental and physical exhaustion.

5. The WESAD study conducted in extremely controlled conditions, as the participants were instructed to not do any "strenuous exercise on the day of the study", and to

"avoid caffeine and tobacco in the hour before the experiment was to begin" [77]. Moreover, the stimuli chosen to induce affect were pre-determined.

6. Cost of the Empatica E4 wristband could be a limitation while conducting research at a large scale, as a single device costs around 1700 USD.

7. As of 7 November 2022, Empatica E4 has been discontinued (https://support.empatica.com/hc/en-us/articles/6093302244637) and in its stead, Empatica has launched the "EmbracePlus" wristband with better sensors and capabilities (https://www.empatica.com/platform/research-studies/).

Summary for Chapter III:

This chapter provides evidence that the biological signals (EDA and BVP specifically), captured from minimally intrusive wearable sensors (such as the E4 wristband) can be used to detect human affective experiences. Features such as the slope and time to rise of the tonic component of EDA, and the number of SCR peaks of the phasic component of EDA, could be of interest. However, prebuilt data processing packages are not always reliable and for future research on EDA signals, and it would be suggested to either employ different peak calculating algorithms or modify the ones proposed in the NeuroKit2 [79]. Additionally, even if the future studies are based on the 'in-the-wild' methodology, self-report instruments will still be needed to capture the dimension of valence while collecting physiological signals [61]. Therefore, it is crucial to explore which self-report measure(s) can be used to study affect (specifically mood) experienced by the older adults. Moreover, it is important to study the frequency in which the participants would be willing to report their moods. This shall be discovered in Chapter IV.

Chapter IV: Qualitative Study

Objectives

This chapter consists of an interview study with the residents of a long-term care facility (Perley Health), to investigate the following research questions:

> RQ2: To find out which self-report measure of mood is preferred by older adults and why?
>
> RQ3: How frequently would the older adults feel comfortable in reporting their moods daily?
>
> RQ4: Which format (electronic or paper-based) would older adults prefer to self-report?

Hypothesis

The hypothesis followed for the interview study was that the older adults would prefer a pictorial measure (either of VAMS-R or Pick-A-Mood), because they were easy to understand and took less time to complete.

Research Design

This study used a qualitative research design. Qualitative studies aim to "provide a rich, contextualized understanding of human experience through the intensive study of particular cases" [80]. Semi-structured interviews, a type of data collection methodology employed in qualitative research studies, typically span from 30 minutes to 1 hour, and require the respondents "to answer preset open-ended questions" [81]. For this research semi-structured interviews were ideal, as they allow the interviewer to explore the core questions in a guided format [81] by engaging in a two-way communication, which maintains the participant privacy (as compared to focus groups where one-to-many communication occurs).

The inclusion criteria for the participants to be a part of this study, were to be (1) aged 65 years and older, living independently or with minimal support at the Perley Health center, (2) able to communicate, read and write in English, (3) understand the purpose of the study and agree to participate in the study, and (4) to provide informed consent. Approval to conduct this research was obtained from the University of Ottawa's Research Ethics Board with the file number H-05-22-8078. Moreover, a Vulnerable Sector Check was obtained from the Ottawa police to conduct the research at Perley Health with the application number 2022-15350759.

The sample size cannot be determined before starting the research, although thematic saturation ("the point in data collection when no additional issues or insights are identified and data begin to repeat so that further data collection is redundant, signifying that an adequate sample size is reached" [82]) is considered to be an ideal stopping point. As per scholarly literature [82], a sample size of 9-17 is ample for thematic saturation for interviews.

The initial pitch for recruitment was delivered to the tenants of building A and building B of Perley Heath during a coffee break in their respective common rooms. The recruitment fliers were circulated and interested participants were given a copy of the consent form to study. They were also asked for a time and place suitable in their schedule for the semi-structured interviews. Also, the recruitment fliers were given to the research coordinator (Nikita Rayne) at Perley Health, who distributed them among the residents of Perley Health. Interested residents were explained the research purpose by the principal investigator and provided with a consent form. Time and place to a participant's preference for the interview were also noted. We intended to recruit 10 participants (irrespective of gender). A total of 11 participants were interested, so one more participant was included in the study. The demographic information collected from the participants is displayed in Table 10.

Participant	Age (years)	Gender	Highest level of education
P1	66	Female	Post-secondary
P2	85	Male	Post-secondary
P3	69	Female	Post-secondary
P4	91	Male	Secondary
P5	78	Female	Post-secondary
P6	84	Male	Post-secondary
P7	90	Male	Post-secondary
P8	72	Male	Post-secondary
P9	82	Female	Secondary
P10	81	Female	Post-secondary
P11	78	Male	Secondary

Table 10: Demographic information for participants in the qualitative study.

Methodology

At the time of the interviews, two copies of the consent form were signed by both the participants and the principal investigator. One copy was given to the participants, and one copy was retained for our records.

The semi-structured interviews with each of the 11 recruited participants were taken individually in a face-to-face conversation, although sometimes non-participants (such as family members, caregivers, or other residents) were present in the surroundings. 5 of the interviews were conducted in respective residential apartments, 2 in a conference room, and 4 in common areas (a garden, a shared lounge, a coffee room, and a recreational room). The interviews were structured in a 4-part format, where in the first part (Part 1), the participants were inquired about their demographic information on age, gender and highest level of education received, reported in Table 10. Part 2 focused on general questions about a participant's mood. Part 3 involved filling out the three self-report questionnaires, and the feedback on the self-report questionnaires was collected in Part 4. The complete interview script is provided in Appendix A.

Specifically, Part 1 aimed to verify the age of participants (65+ or not), record their literacy level and their familiarity with technology. Part 2 investigated daily moods and related behaviors of the participants, along with their preferences on conveying their moods, such as frequency of communication, the medium of communication used etc. This was done to explore how the participants manage their daily moods, whether they feel reserved about expressing their moods to other people. Part 3 and 4 tested the selected self-report questionnaires with the participants to obtain their preferences and thus verify our hypothesis.

To reduce the question order bias, the sequence of administration of the questionnaires was randomized for each participant, by randomly shuffling the digits '1', '2', '3' using a Python program, where '1' represented POMS 2 SF A, '2' represented VAMS-R, '3' represented Pick-A-Mood. The snippets for the program are attached in Figure 12.

```python
import random

l = ['1','2','3']
for i in range(1,12):
    random.shuffle(l)
    n = ''.join(l)
    print(f"Order for P{i}: {n}")
```

```
Order for P1: 132
Order for P2: 231
Order for P3: 312
Order for P4: 321
Order for P5: 132
Order for P6: 132
Order for P7: 213
Order for P8: 132
Order for P9: 321
Order for P10: 213
Order for P11: 123
```

Figure 12: Randomization of the order of administration for self-report measures.

Moreover, all the male participants were administered with the male cartoon-based Pick-A-Mood scale, and all the females were a shown a female cartoon-based version. Since, all the participants identified their gender binarily (male and female), the robot-based version was not administered.

The interviews with each participant were audio recorded using the default voice recording application ("Voice Memos") in iPhone 13, where each recording was saved with the alphanumeric code given to the respective participant (e.g., P1 for participant one). Transcription of the interviews was done by a single coder (principal investigator) in Microsoft 365 Word and structured into four parts (as per the interview script). The transcripts were cleaned to omit private information (like name and location of residence), word repetitions, grammatical errors, and irrelevant (words as well as sentences) or repetitive information (such as introduction to the study). Additionally, the instrument information as well as actual responses to the POMS 2-Adult Short were omitted from both the transcripts, because the verbal items in POMS 2 Adult Short are protected by Multi Health Systems copyright (https://mhs.com/permissions-translations-and-licensing/). Also, the test-specific assessment reports (for all three tests) were not calculated for the responses provided by the participants, as we were only interested in the feedback (qualitative data) on the self-report questionnaires.

Data analysis

For this research thematic analysis was chosen to analyze the data over content analysis, as the latter focuses more on quantification of data (coding and frequencies), whereas the former focuses on uncovering themes and underlying relationships in textual data [83]. Thematic analysis has been defined as a method to deduce (identify, analyze and report) the themes or patterns existing in data [84]. A theme is described as something which captures evidence from the data in regard to the research question while representing a pattern across the whole data set.

Braun and Clarke [84] provided a six-step framework to perform thematic analysis. The first step requires researchers to familiarize themselves with the data by transcribing, reading, and making initial notes. The second step is concerned with generating initial codes gathering relevant data for respective codes. The third step combines the initial codes into potential themes which are reviewed and refined in the fourth step on their validity and accuracy on forming pattern with other themes and the data set as a whole. The refined themes are then properly defined and named in step five and reported in the last step.

Results and Discussion

Analysis of the transcripts resulted in 20 initial codes, and from these 20 codes, 12 potential themes were derived. Upon examining the potential themes for underlying patterns, 5 final themes were deduced, which are presented below. The range of codes for each theme varied between 1-6 codes. Moreover, wherever possible, the themes are followed with a discussion and recommendations. This was done to improve the readability of the document, in respective contexts. The matrix used for analysis is attached in Appendix D.

Theme 1: Possession of internet-enabled technologies.

The majority of the participants (n=9) possessed internet-enabled technologies (smartphones, tablets, laptops, computers, gaming consoles, or smartwatches), and were familiar with using them, with a typical use case involving communication and leisure.

Theme 2: Genuine expression of feelings in conversations.

It was observed that, not all of the participants genuinely discuss their feelings with the people who they interact with (especially if the interlocutor is random); the reasons being "I'm aware that I can impact the way other people feel, and I don't want to bring people down" [P3], or "To me, it's not an important part of my makeup, discussing how I feel with everybody" [P9], or "If somebody can't do anything about it, I probably wouldn't" [P1]. Moreover, the observed time span between conversations involving sharing of mood and feelings ranged from couple of times a day to once a week to hardly ever.

Infrequent expression of mood states in conversations might lead to accumulation of feelings, and to stress, anxiety, depression, and a state of isolation if the accumulated feelings are negative. Technological solutions can, however, help the older adults to acknowledge their mood states, provide personalized solutions to improve mood (such as music and movie suggestions, food recommendations, light adjustments etc.) and notify caregivers/family members about prolonged episodes of certain mood(s).

Theme 3: Awareness and management of daily moods.

None of the participants maintained a written record (such as a diary) of their daily feelings, and only a few associated specific behaviors with their moods, such as eating or sleeping when bored, overeating when nervous or not feeling energetic due to lack of sleep. It was also noted that the majority of the participants did not experience mood fluctuations in their daily life, and those who did, experienced them only under trigger events, such as the blasting noise of a fire alarm, medical conditions e.g., arthritis, or due to news and media. However, the majority of the participants discussed indulging themselves in activities to manage their mood(s). These activities included playing video games, socialization, singing, whistling, reading the Bible, engaging in discussions and in group activities.

Theme 4: Requirements for mood reporting.

When asked to respond to the assumption that they were to record their moods, it was observed that all but one of the participants who possessed technological devices and were familiar with them (from Theme 1) preferred reporting their mood digitally (online). Moreover, the expected duration of time per mood reporting session ranged from one minute to half an hour, while the frequency of such sessions per day ranged from once a day to 4-5 times a day. Some participants expected the measure to capture spontaneous changes in mood, whereas some participants preferred being notified by an alarm or a reminder to report their moods.

Therefore, we would recommend administering self-report measures as smartphone applications, with flexible features to accommodate both fixed time reporting (and notifying using reminders) or spontaneous reporting, according to user preference. A solution to spontaneous reporting can be seen in Saganowski et al. [85], where the researchers proposed a method to annotate continuous physiological signals by detecting strong affect captured using wearable devices. On detection of a strong signal, a notification would be displayed to participants on their smartphone to fill up an Ecological Momentary Assessment (EMA) questionnaire to register their affective state [85].

Theme 5: Preferred self-report instrument.

Upon analyzing the feedback collected after administering three self-report measures (POMS 2-S A, VAMS-R and Pick-A-Mood), it was noted that six participants preferred the verbal (adjective-based) scale POMS 2-S A over the others, because "it was more in depth" [P1], had a "good variety of words and they express feelings and moods" [P2], was "self-explanatory" [P4], "was more in detail" [P8], was "more analytical than the others" [P9] and was "more to the point, more accurate" [P11]. Two participants preferred VAMS-R because "it was easy to answer. You didn't have to think too much" [P5], and it was "easier to follow" [P7]. Only one participant, [P3], preferred Pick-A-Mood, as it was straightforward and expressions on the faces could be seen immediately. Two participants, however, did not prefer any scale over the other, but when specifically asked to choose one for daily self-report, chose Pick-A-Mood as it was "straightforward" [P6] and POMS 2-S A [P10]. In conclusion, the hypothesis that the older adults would prefer pictorial scales over adjective-based scale failed for this batch of participants.

	POMS 2-S A	VAMS-R	Pick-A-Mood
Participants	7	2	2

Table 11: Self-report measures preferred or chosen by the participants for daily use.

It is important to note that P10 found Pick-A-Mood hard to use as "it just didn't appeal to me as a way of describing my mood. I thought the questions were better than the pictures" [P10], and VAMS-R was disliked by P3 due to its vertical orientation and P11 as it was "not accurate" [P11].

A prototype self-report questionnaire

From the interview study it was inferred that most of the participants favoured the adjective based scale for self-reporting their mood over pictorial scales. Although we recommend using adjective based measures in the future research, we would not suggest using POMS derived scales due to their limitation of originally being constructed for psychiatric patients to capture specific mood states and not to cover the global dimensions of affect [86].

Prototyping "is defined as the process of developing a working replication of a product or system that has to be engineered" [87]. Following the first step of the prototyping model [87] of the software development life cycle (SDLC), we have gathered and analysed the user requirements from the interview study. As per the second and third steps [87], we propose an adjective based self-report measure prototype (Table 12). Taking inspiration from the works of Sakairi et al. [88], who derived a two-dimensional adjective based mood scale from Japanese versions of mood scales, our prototype is built on the 8 distinct moods of Pick-A-Mood by Desmet et al. [21], who follow the 2-dimensional theory of affect. Each mood expression in the proposed scale (2 expressions per quadrant of affect), has been expressed using three adjectives. This scale could be administered digitally and be rated on a 5-point Likert scale to capture granularity. Only 24-items in this scale imply it would be quick to administer.

We have not prototyped a translated scale (i.e., English translation of Japanese from Sakairi et al. [88]), as translations do not accurately capture cultural contexts. Instead, in the prototype we propose, the adjectives for each of the mood expression were selected from the thesaurus of the English language. The selection criteria for the mood-adjectives was based on the discussion by Desmet et al. [21], who provided the differentiation that "emotions always imply and involve a relation with a particular event, person or object", whereas "moods are not directed at a particular object but rather at the surroundings in general".

Mood states [21]	Adjectives	Not at all (1)	Slightly (2)	Moderately (3)	Very much (4)	Extremely (5)
Excited	Exhilarated					
	Overjoyed					
	Elated					
Cheerful	Cheery					
	Upbeat					
	Joyful					
Relaxed	Comfortable					
	Relieved					
	Rested					
Calm	Tranquil					
	Serene					
	Peaceful					
Sad	Gloomy					
	Unhappy					
	Sorrowful					
Bored	Worn-out					
	Weary					
	Jaded					
Irritated	Frustrated					
	Bothered					
	Cranky					
Tense	Anxious					
	Jittery					
	Uneasy					

Table 12: Proposed adjective-based mood reporting instrument.

Nevertheless, before using this scale in research, it is important to conduct user evaluation with the target population (step 4 [87]), refine the prototype (step 5 [87]), and verify its psychometric properties (reliability and validity).

Limitations

1. The sample size of recruited participants was small. Therefore, a statistically significant conclusion about the preferred measure of mood among older adults could not be made.

2. A possibility of sampling bias exists, as participants were not randomly selected from the population of interest. They may not fully represent the residents at long-term care centers.

3. During the user evaluation of Pick-A-Mood scale, the male participants were only shown the male cartoons and the female participants were only shown the female cartoons. The reason for this was that the participants only identified binarily (i.e., either male or female), and the Pick-A-Mood scale showed no significant gender effect ("with multivariate ANOVA's with gender as independent and valance and arousal as dependent variables" [21]). However, as the participants were not asked whether they would like to be a shown a different scale (opposite to their gender), this could have introduced research bias in the study.

Chapter V: Conclusion

This thesis contributed towards exploring a potential enhancement (context-awareness) for the ambient assisted living (AAL) technologies using affective computing. Particularly:

In Chapter III, evidence was obtained that biological signals captured from minimally intrusive wearable sensors, such as the E4 wristband, can be used to detect human affective experiences. Specifically, the LF/HF ratio feature obtained from Blood Volume Pulse signal, and the slope and peak values of the tonic component obtained from the Electrodermal activity (EDA) signal looked promising and should be explored in future research.

The qualitative study in Chapter IV, explored the preferences and perspectives of older adults towards self-report measures of mood, while probing for the acceptance and feasibility of the measures. Feasibility was determined by selecting the measures that were understandable to the target population, that could be completed in a reasonable amount of time, and whose results could be correlated with signals from sensor devices. Acceptability was assessed by asking the participants which measure they preferred in the interviews. Majority of the participants preferred the verbal scale (POMS-2 SF A) due to its accuracy, detail, and thoroughness, and thus, the hypothesis that the older adults would prefer pictorial scales over adjective-based scale failed. Moreover, 8 of 9 users of technology stated their preference to use a digital scale (to be administered on an electronic device), with the frequency of reporting ranging from once to 4-5 times a day.

Potential risks associated with affective computing

Before concluding, it is important to highlight the potential risks that are associated with affective computing, some of which are:

1. Emotional dependency: Continuous reliance on emotional assistance can negatively impact an individual's ability to independently manage their emotional well-being, leading to a dependence on affective devices for sustenance and regulation of emotions [89].
2. Emotional manipulation: The ability to detect and recognize emotional states of users can be misused to exploit their vulnerabilities [89]. E.g., a system can recognize stress and suggest smoking cigarettes as a solution.
3. Privacy concerns: People regard emotional data as personal and prefer to keep it private [89], which was confirmed in Chapter IV, Theme 2 of this thesis. Unauthorized access to such information (e.g., by marketing companies) can breach user's privacy [89]. Also, the risk of sensitive data being hacked or stolen is always prevalent.
4. Altered human relationships: Humans "attach and connect to each other strongly through emotion" [89]. Bringing emotionally intelligent systems into mainstream care provision might alter the perception of individuals towards human relationships [89].

Implications for future research

To apply affective computing in engineering solutions, we recommend to use the iterative design model which "focuses on an initial, simplified implementation, which then progressively gains more complexity and a broader feature set until the final system is complete" [90]. Design modifications and new functionalities are added incrementally (small portions at a time) and iteratively (i.e., in repeated cycles) to the application being developed, while simultaneously validation and verification of the application is conducted throughout every iteration [91]. Moreover, this process produces a working model at early stages of development, which enables engineers to detect and correct any flaws or defects early on, thus saving costs [91]. Also, the results of each iteration can be used to direct the course of action of development, i.e., stopping the development process prematurely if undesirable outcomes are obtained.

Using this approach, under the assumption that future applications will use multi-modal sensor devices and the "in-the-wild" methodology, we describe iterative three phases for successful execution of affective engineering:

1. Phase 1: Finding signals of interest.
   This phase will help in determining the signals of interest which are capable of detecting the arousal dimension of affect. The focus should be on differentiating between two basic arousal states: excited/de-excited and neutral, based on physiological data collected from wearable sensor devices. The self-report measure at this stage should only have two or three selections.

2. Phase 2: Detecting basic affective states.
   This phase should utilize simple dimensional self-report measures with limited affective states, such as the Pick-A-Mood [21] scale. Moreover, unsupervised machine learning models, such as K-Means clustering should be employed on affective data, to verify whether the detected mood clusters fall in the quadrants of the dimensional model used for annotation, or to explore if clusters overlap or are missing.

3. Phase 3: Differentiating between affective states.
   Nuanced self-report measures (i.e., verbal measures) should be used in this phase to detect distinct moods such as the one proposed in Table 12, while employing complex supervised machine learning algorithms, or even ensemble methods (i.e., multiple learning models) to obtain the best predictive performance.

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Appendix A: Supplementary Documents

Recruitment Flyer:

ARE YOU INTERESTED IN PARTICIPATING IN A RESEARCH STUDY ON ACCURATELY RECORDING DAILY MOOD?

We would like to find out the needs and requirements of older adults for developing a user-centred self-report measure that accurately captures their experienced mood(s) in real time.

If you participate, you will be asked to participate in a 30-minute, one-on-one interview with a 15-minute session with questions on mood, followed by a 15-minute assessment of 3 existing self-report measures for mood.

The interviews will take place according to your preference, either in your apartment or in a common area. We will be recruiting on a first-come, first- served basis for a range of 5-10 participants.

YOU ARE ELIGIBLE IF YOU ARE:

- Living in an apartment at the Perley Health.
- Able to communicate, read and write in English.
- 65 years of age or older.
- Able to provide informed consent.
- Able to answer questions about your mood and lifestyle.

If you are willing to participate, please contact:

Devvrat Bhardwaj
(Principal Investigator)
TELEPHONE: PII
EMAIL: PII

Nikita Rayne
(Research Coordinator)
TELEPHONE: PII
EMAIL: PII

For more information, please contact the project supervisors

Dr. Pascal Fallavollita
TELEPHONE: PII
EMAIL: PII

Dr. Jeffrey Jutai
TELEPHONE: PII
EMAIL: PII

Certificate of Ethics Approval:

13/07/2022

Université d'Ottawa
Bureau d'éthique et d'intégrité de la recherche

University of Ottawa
Office of Research Ethics and Integrity

CERTIFICAT D'APPROBATION ÉTHIQUE | CERTIFICATE OF ETHICS APPROVAL

Numéro du dossier / Ethics File Number	H-05-22-8078
Titre du projet / Project Title	Implementation of self-report measures to accurately capture older adults' daily mood and behaviors.
Type de projet / Project Type	Thèse de maîtrise / Master's thesis
Statut du projet / Project Status	Approuvé / Approved
Date d'approbation (jj/mm/aaaa) / Approval Date (dd/mm/yyyy)	13/07/2022
Date d'expiration (jj/mm/aaaa) / Expiry Date (dd/mm/yyyy)	12/07/2023

Équipe de recherche / Research Team

Chercheur / Researcher	Affiliation	Role
Devvrat BHARDWAJ	École de science informatique et de génie électrique / School of Electrical Engineering and Computer Science	Chercheur Principal / Principal Investigator
Pascal FALLAVOLLITA	École interdisciplinaire des sciences de la santé / Interdisciplinary School of Health Sciences	Superviseur / Supervisor
Jeffrey JUTAI	École interdisciplinaire des sciences de la santé / Interdisciplinary School of Health Sciences	Co-superviseur / Co-supervisor
Danielle SINDEN	The Perley and Rideau Veterans' Health Centre	Autre / Other

Conditions spéciales ou commentaires / Special conditions or comments

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Interview Script

Introduction

Hello,

I’m Devvrat Bhardwaj, a master’s student at the University of Ottawa, and I’m the principal investigator of this research. Thank you for joining me today, I really appreciate you sharing your time to come in and talk to me. The first thing I’d like you to do is to read through this study informed consent sheet, which explains the purpose of the study and how the data is collected and stored. After you’ve read through it, I can answer any questions you have.

As stated in the consent sheet, I’ll be audio recording the interview. Do you agree to participate in this study, and be audio recorded?

PART 1. Demographic questions

Before we start with the interview, I’d like to ask you some demographic questions.

Q1. How do you identify yourself in regard to gender? (Male/Female/Other/Prefer not to say)

Q2. How old are you?

Q3. What is your highest level of education? (High school/ Bachelor’s Degree/ Master’s degree/ Ph.D. or higher/ Other (please specify) / Prefer not to say)

Q4. Do you possess a smartphone? What do you use it for?

PART 2. Questions about mood

****Keep the sentences short and simple to make sure they understand and are clear/comfortable**

Let’s get started. Just to remind you, there are no right or wrong answers to any of the questions today. We’re really interested in learning about everyone’s unique experiences. You are the expert. We are here to understand your perspectives and experiences, so we will not be sharing our opinions. I will be asking you questions and writing down notes on your responses to the questions.

As you read in the study consent sheet, the objective of this research project is to develop an accurate self-report measure for recording the moods experienced by older adults, in day-to-day life.

1. How would you respond when somebody asks you “How are you doing?”.
    a. Would you honestly express your mood, or try to skip the conversation?
    b. Does it matter whether it is somebody you know well or a stranger?

If they do express their mood, then

   c. How do you prefer expressing your mood?
      i. Verbal, facial expressions, text messages, emojis, talk it out, write in a personal diary, smartphone app?
      ii. Are there particular things you do depending on your mood? (Eat something, go to the gym for exercising, draw, sing etc.)

2. On a daily basis, how often are you asked about your mood? (To determine the frequency of mood reporting)
   a. Who asks for it?
      i. Friend/family/doctor/caregiver/stranger
      ii. Some kind of device or app (diary, smartphone app etc.)
         1. If self-reporting app, then questions on the likes and dislikes, as well as on the requirement of such app, could be followed.

3. Do you think your moods change a lot within a day?
   a. Would you find it helpful to record and review your moods and behaviours?
   b. If yes, then how frequently would you be comfortable to log in your mood per day?
      i. Multiple times a day?
      ii. Or during specific life events (particularly stressful phases in life)?

4. If you were to log in your daily mood,

   a. Would you prefer to do it on a paper-based format, or in an online format on your smartphone?
   b. Would you prefer a specific time for logging mood in? (e.g., after waking up, before lunch)? (Fixed time or flexible)
   c. Would you like to be prompted/notified (such as with a sound or alarm) to log in current mood and behaviour?
   d. How much time do you think it should take to log your mood?

PART 3. Mood questionnaires

****Turn the laptop away. Only show them the tests. Use the predetermined order of sequence.**

Now, I have 3 different mood questionnaires that I would like you to complete.

1. **Profile Of Mood States Second edition (POMS 2) – Adults Short form**

   The Profile of Mood States Second Edition (POMS 2) instruments assess the mood states of individuals 13 years of age and older.

POMS 2 – A Short, consisting of 35 items, requiring 3 to 5 minutes. Each question is tested on a granularity of 1-5, where:

1	**Not at all**
2	**A little**
3	**Moderately**
4	**Quite a bit**
5	**Extremely**

2. **Visual Analogue Mood Scale - Revised (VAMS – R)**
   a. **Examples must be close to the original study**
   The VAMS is a reliable and valid measure of eight specific mood states: Afraid, Confused, Sad, Angry, Energetic, Tired, Happy, and Tense. The scales have a "neutral" schematic face (and accompanying word) at one end of a 100 mm vertical line and a specific "mood" face (and word) at the other end of the line. Respondents indicate the point along the vertical line that best describes how they are currently feeling. The score for each mood ranges from 0 to 100, with 100 representing a maximal level of that mood and zero representing a minimal level (or absence) of that mood.

3. **Pick-A-Mood**
   a. **Studies with older adults.**
   Pick-A-Mood is a character-based pictorial scale for mood expression and measurement. The cartoon characters enable people to express their moods quickly, intuitively, and accurately. The characters express eight different mood states (and one neutral state), representing four main mood categories: Excited & Cheerful (for energized-pleasant); Irritated & Tense (for energized-unpleasant); Relaxed & Calm (for calm-pleasant); Bored & Sad (for calm-unpleasant).

PART 4. Feedback on mood questionnaires

**** Try to avoid yes and no answers. Let them explain**
**** Remind participants about the measures using slides/layout**

Now I'd like to ask you for your opinions about these questionnaires.

1. Which one of the questionnaires was the easiest for you to understand? Tell me more about that?
2. Which one was the hardest to understand? Why…
3. Which one did you like the most? What do you like about it?
4. Which one did you like the least? What do you dislike about it?
5. For the one you like the best, if you had a choice between completing it in paper form or on a smartphone or tablet, which method would you choose?

Informed Consent Form for Perley Health Tenants

uOttawa

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Ottawa ON K1N 6N5 Canada

Date: 17 June, 2022

Research study title: Implementation of self-report measures to accurately capture older adults' daily mood and behaviors.

Name and contact information of researchers:

Devvrat Bhardwaj, Principal Investigator, MASc Electrical and Computer Engineering, Faculty of Engineering, University of Ottawa, Contact: PII

Professor Pascal Fallavollita, Project Supervisor, Interdisciplinary School of Health Sciences, Faculty of Health Sciences, University of Ottawa, Contact: PII

Professor Jeffrey Jutai, Project Co-supervisor, Interdisciplinary School of Health Sciences, Faculty of Health Sciences, University of Ottawa, Contact: PII

Office Address: University of Ottawa, 200 Lees Av, Ottawa, ON, Canada, K1S 5S9

Research Funding Provided by:
MITACS PATH (Program to Accelerate Technologies for Homecare) project.

Research ethics board approval:
Date of Approval: 13th July 2022
Study#: H-05-22-8078

Invitation to participate

You are invited to participate in this master's thesis research project because you are a tenant at Pearly Health. Even though this research takes place at Perley Health, the study is independent of Perley Health. The information in this form is intended to help you understand what we, the uOttawa research team, are asking of you so that you can decide whether you agree to participate in this study or not. Your participation in this study is **completely voluntary,** and a decision not to participate will not affect the nature, amounts, and quality of services you receive from Perley Health. As you read this form and decide whether to participate, please ask any questions you have, take whatever time you need, and consult with others as you wish.

Purpose of the Research:

This project is a part of the Program to Accelerate Technologies for Homecare (PATH), which is facilitated through MITACS.

The purpose of this project is to improve the overall wellbeing of older adults by focusing on their hedonic wellbeing (associated with their feelings and mood), via mobile health (mHealth) technological interventions. The objective of this research project is to develop a self-report measure for recording the moods and behaviors experienced by the older adults, in day-to-day life. For this project, you will be asked to participate in a one-on-one **30-minute semi-structured interview**, where you will be asked to share your opinions, perspectives, expectations, and requirements from the self-report measure being developed.

Please note that the semi-structured interview will be audio recorded for the full 30-minute session.

The purpose of creating a user-centered self-report mood and behavior assessment tool, is to reduce the limitations seen in already existing mood and behavior measures, which include but are not limited to burden/fatigue experienced in filling long-item classical measures multiple times a day, inflexible, complex, and non-intuitive interfaces, and the existence of retrospective bias in daily reports.

Who can take part in this research study?

To participate in this study, you must be a tenant living at the Perley Health Centre. The inclusion criteria are: (1) aged 65 years and older, (2) able to communicate, read and write in English, (3) understanding the purpose of the study and agreeing to participate in the study, and (4) willing to provide information under informed consent.

Risks and Discomforts:

We do not anticipate any risks to participating in this study.

Benefits of the Research and Benefits to You:

The participants will help in the development of a user-centered self-report tool to capture their moods and behavior. We will explain that, while there may be no direct benefits to participants, the captured information can help the researchers to develop better ways of providing mood management and personalized care to persons like them.

Compensation/Reimbursement:

You will not receive compensation for being a part of this study.

Privacy and Confidentiality:

If you decide to participate in this study, confirmed by your signature on this document, you will be assigned a unique alphanumeric identification number (ID). All data obtained from this study will be labelled with your unique ID, meaning no identifying information (such as your name, age, gender, e-mail) will be retained for this study. We will not collect any personal information from you other than your age and gender.

Any information you supply during the research will be held in confidence among the uOttawa research team. The interview's audio recordings and subsequent transcriptions will be stored locally in an encrypted format on the uOttawa research team's password-encrypted computers and on an encrypted flash drive that will be kept in a locked cabinet in the research team's lab. Additionally, only the core research team members will have access to this information. We will password protect any research data that we store or transfer.

> *The data collected in this research project may be used – in an anonymized form - by members of the research team in subsequent research investigations exploring similar lines of inquiry. Such projects will still undergo ethics review by the uOttawa REB. The research team will treat any secondary use of anonymized data with the same degree of confidentiality and anonymity as in the original research project. The data collected from this research will be conserved for 6 years. After 6 years, all physical and electronic data will be destroyed. All physical data will be shredded using the appropriate confidential shredding protocol, and all electronic data will be deleted off the lead researcher's computer and back-up drive using the secure deletion protocol.*

Withdrawing from the study

Your participation in the study is **entirely voluntary**, so you are under no obligation to participate in this study once it has started. You are free to withdraw from the study at any time with no explanation required. Your decision to withdraw from this study will have no negative impact on any of the relationships you have at the Pearly Centre or with any of the researchers conducting this study.

If you decide to withdraw from this study at any time, all of the data pertaining to your involvement will be removed and will not be available to use for further research. If the results of the study are published, no information that discloses your identity will be released or published, without your specific consent to the disclosure. All data will only be reviewed by members of the research team and will be destroyed after 6 years.

Conflicts of Interest

There are no conflicts of interest that the researchers are aware of that relate to this study.

Questions About the Research?

If you have questions about the research in general or your role in the study, please feel free to contact the Principal Investigator, Devvrat Bhardwaj, either by telephone at PII or by email at PII. You can also contact the supervisors (their contact information is provided on the top of this form). This study has been reviewed and approved by the University of Ottawa's Research Ethics Board and conforms to the standards of the Canadian Tri-Council Research Ethics guidelines. If you have any questions about this process or your rights as a participant in this study, please contact the Office of Research Ethics and Integrity at the University of Ottawa, located in Tabaret Hall, room 154, or telephone (613-562-5387), or e-mail (ethics@uottawa.ca).

This research study was reviewed and approved by the University of Ottawa Research Ethics Board.
Legal Rights and Signatures:

I ……………., consent to participate in the *Implementation of self-report measures to accurately capture older adults' daily mood and behaviors* study conducted by Devvrat Bhardwaj and the uOttawa Research team. I have understood the nature of this project and wish to participate. There are two copies of the consent form, one of which is mine to keep. However, I know that I am not waiving any of my legal rights by signing this form. Therefore, my signature below indicates my consent.

Additional consent

1. **Audio recording**

- ☐ I consent to the audio recording of my participation in the semi-structured interview.
- ☐ I do not consent to the audio recording of my participation in the semi-structured interview.

Signature ______________________ **Date** ____________________
Participant

I have discussed this study in detail with the participant. I believe the participant understands what is involved in this study. I confirm that the participant was given an opportunity to ask any questions or raise any concerns they may have, and I answered those questions to the best of my ability. I confirm that the individual has not been deceived or coerced in any way and has given consent freely and voluntarily. I will ensure that the participant receives a copy of this form.

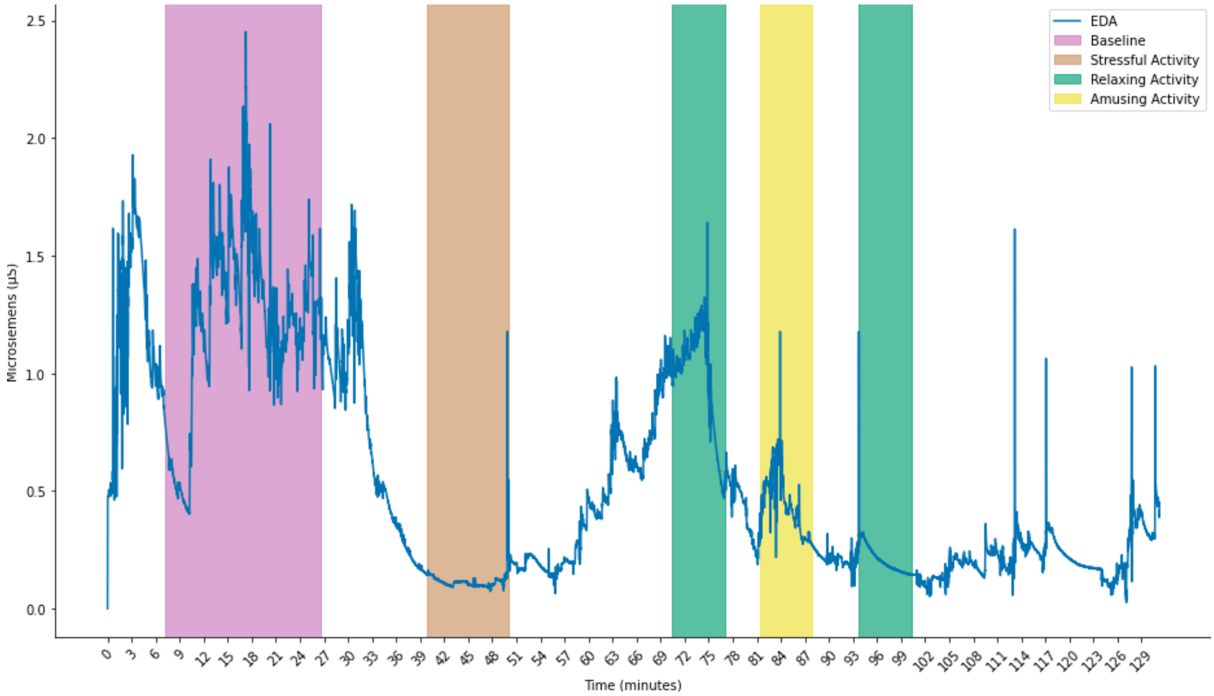
Signature______________________ **Date____________________**

Principal Investigator

Appendix B: Exploratory Data Analysis on the WESAD dataset [77].

Subject 2 (S2)

EDA Visualization for S2:



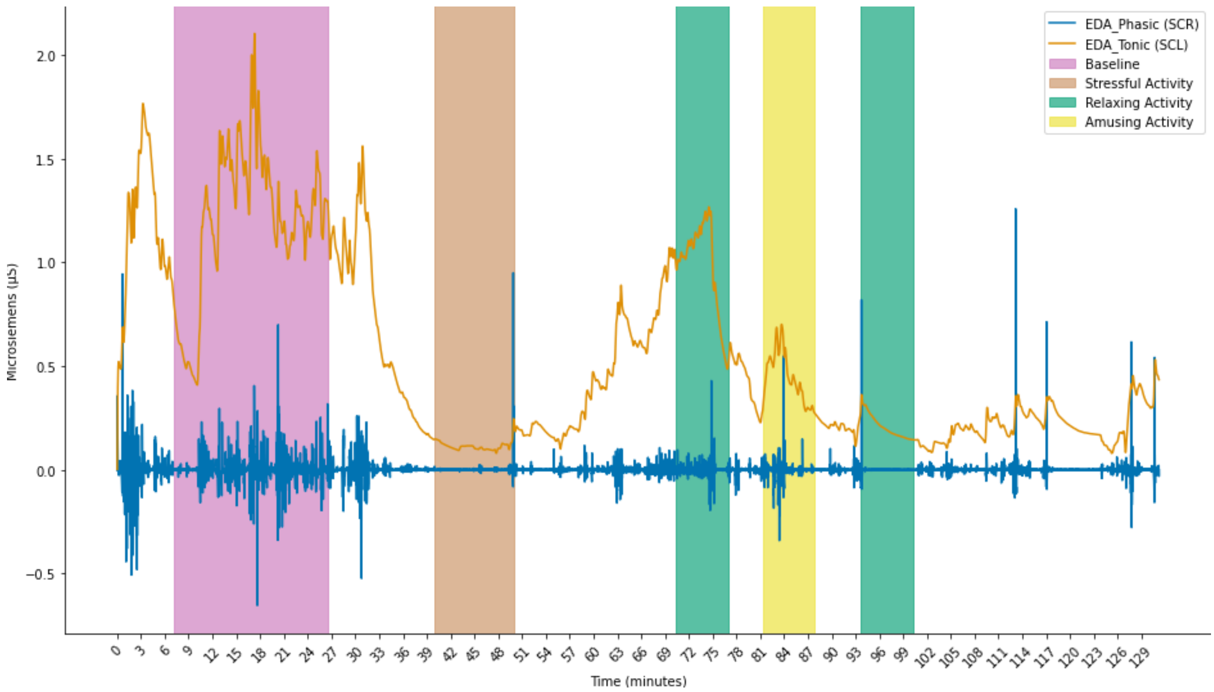


Figure 13: EDA visualization for S2: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S2:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	0.698104251	0.114234257	0.44516844	0.980755548	0.452889623	0.209086095
eda_std	0.412346824	0.032464173	0.275571255	0.227068631	0.124233876	0.066662921
eda_min	0.143776	0.074584	0.065615	0.468022	0.218093	0.142495
eda_max	1.717419	1.17781	1.159941	1.64182	1.17781	1.17781
temp_mean	35.7740312	35.75918619	34.59663784	32.66927906	33.06924133	34.29040906
temp_std	0.104894147	0.135102507	0.71900825	0.300933666	0.087641579	0.250344802
temp_min	35.49	35.5	33.29	32.31	32.81	33.97
temp_max	35.93	35.97	35.53	33.33	33.29	34.66

Table 13: EDA and Temperature features for S2

HRV Features for S2:

Extracted_Features	S2_Neutral	S2_Stressed	S2_Amused
HRV_MeanNN	879.0211397	834.7592807	858.889055
HRV_SDNN	282.0273795	185.4559417	411.4983596
HRV_SDANN1	48.74548792	48.64517615	49.22002255
HRV_RMSSD	383.9759669	253.5002064	567.6581419
HRV_pNN50	65.44117647	57.54060325	88.99521531
HRV_LF	0.035543438	0.0267838	0.033616727
HRV_HF	0.023529456	0.068573027	0.012155012
HRV_LFHF	1.510593266	0.390587978	2.765667867

Table 14: HRV features for S2

Subject 3 (S3)

EDA Visualization for S3:

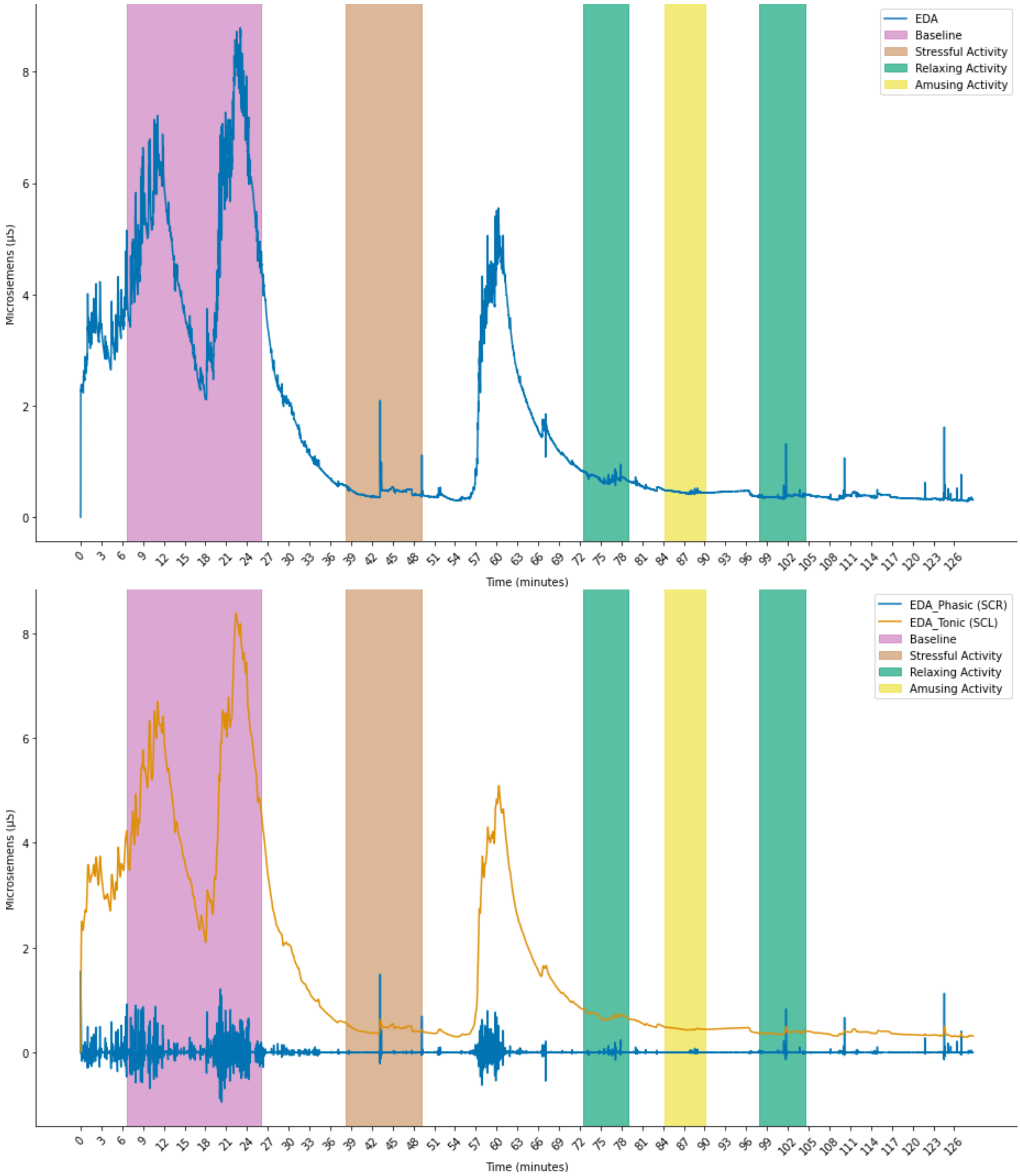


Figure 14: EDA visualization for S3: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S3:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	1.6339823	0.445804828	1.669038445	0.697514743	0.449593742	0.374245291
eda_std	0.9972339	0.075230212	1.39429214	0.058005557	0.017649504	0.04643179
eda_min	0.555119	0.355174	0.292393	0.570494	0.411549	0.326987
eda_max	4.695138	2.095285	5.55524	0.949745	0.520456	1.316184
temp_mean	33.01025	33.20402878	32.31627134	31.43723593	30.75059957	30.69488387
temp_std	0.2592349	0.051910613	0.467785425	0.128932809	0.157012382	0.149052676
temp_min	32.63	33.11	31.59	31.19	30.47	30.37
temp_max	33.47	33.31	33.16	31.65	31.03	30.89

Table 15: EDA and Temperature features for S3

HRV Features for S3:

Extracted_Features	S3_Neutral	S3_Stressed	S3_Amused
HRV_MeanNN	981.8989071	1058.766593	1068.211858
HRV_SDNN	293.2021003	553.28401	812.503081
HRV_SDANN1	97.71615428	319.1538673	416.7335981
HRV_RMSSD	334.3395913	631.9201306	1059.608853
HRV_pNN50	86.06557377	84.07079646	85.19637462
HRV_LF	0.023079893	0.013194128	0.012513861
HRV_HF	0.04011144	0.003031289	0.000941874
HRV_LFHF	0.575394286	4.352645349	13.28612573

Table 16: HRV features for S3

Subject 4 (S4)

EDA Visualization for S4:

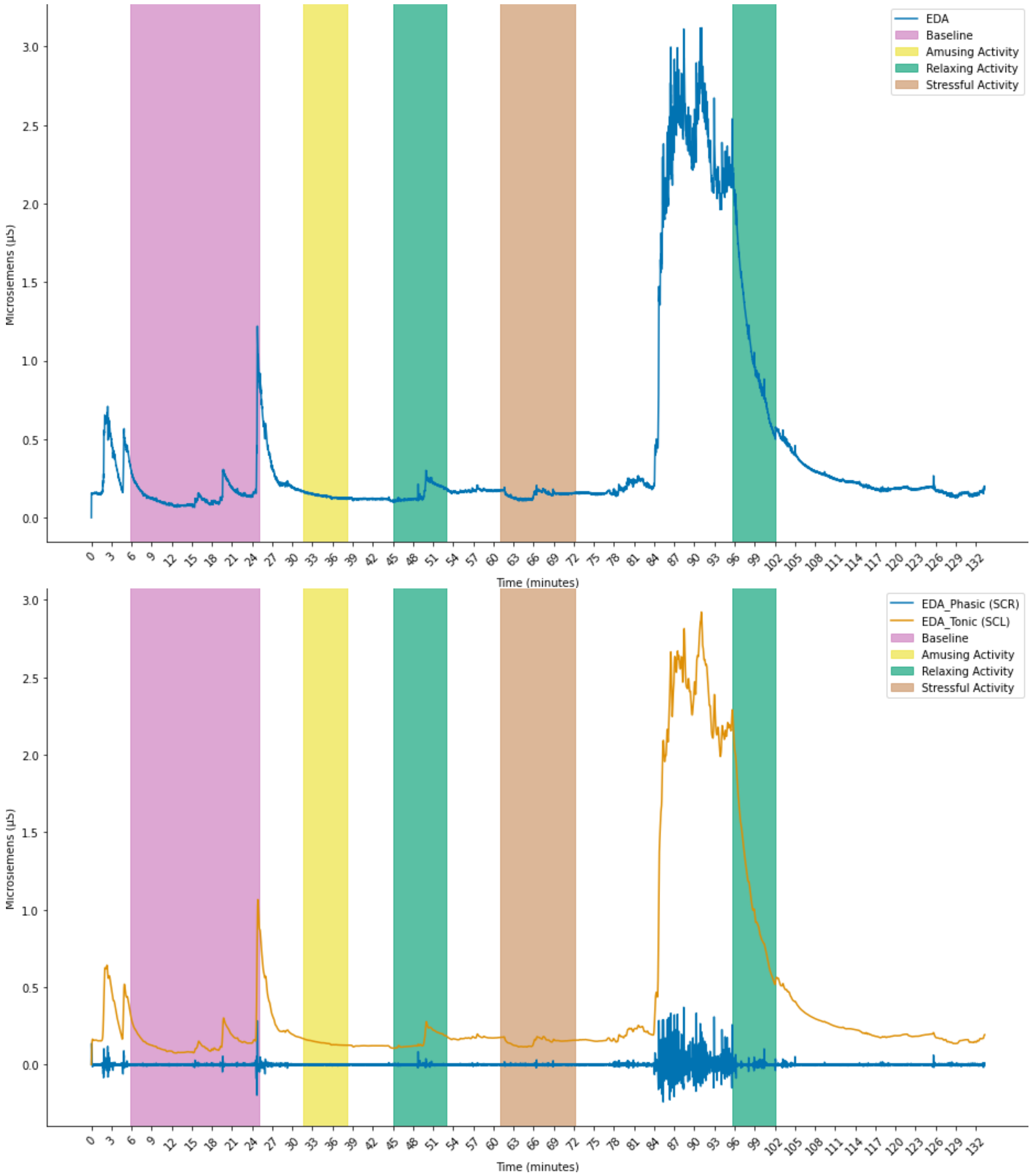


Figure 15: EDA visualization for S4: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S4:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	0.3131825	0.139323958	0.158218885	0.146881342	1.202008897	1.113279311
eda_std	0.1830185	0.012447414	0.051228251	0.020742172	1.088343892	0.458161896
eda_min	0.164001	0.116671	0.098763	0.106438	0.137138	0.508168
eda_max	0.920062	0.167838	0.300872	0.206214	3.119045	2.229714
temp_mean	32.624813	32.9250733	33.04270172	32.86740438	32.61599822	32.1095541
temp_std	0.1700773	0.035112644	0.048511836	0.095444621	0.19159254	0.078701331
temp_min	32.43	32.87	32.97	32.68	32.15	31.93
temp_max	32.93	33	33.13	33	32.89	32.23

Table 17: EDA and Temperature features for S4

HRV Features for S4:

Extracted_Features	S4_Neutral	S4_Amused	S4_Stressed
HRV_MeanNN	919.9919872	972.4762873	943.6266447
HRV_SDNN	318.6723104	204.8341645	226.3460638
HRV_SDANN1	38.99477102	46.85802402	47.67548459
HRV_RMSSD	458.5859817	293.181535	320.5168097
HRV_pNN50	79.23076923	78.3197832	77.10526316
HRV_LF	0.052468223	0.016265944	0.024542932
HRV_HF	0.01564443	0.072263205	0.091781283
HRV_LFHF	3.35379574	0.225093028	0.267406717

Table 18: HRV features for S4

Subject 5 (S5)

EDA Visualization for S5:

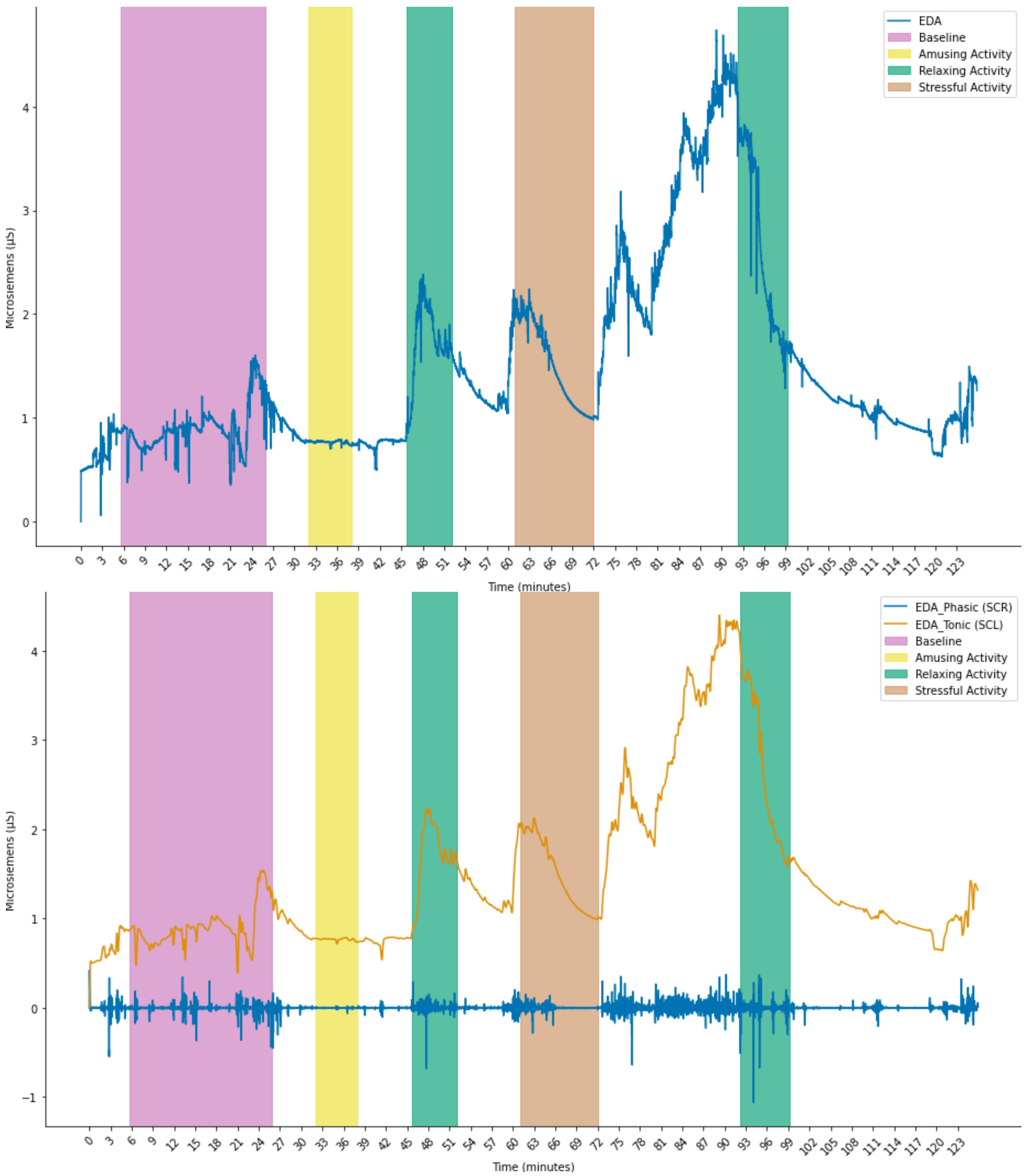


Figure 16: EDA visualization for S5: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S5:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	0.9365627	0.767052864	1.730517996	1.512306042	2.906584481	2.66331054
eda_std	0.1348453	0.014745752	0.374668064	0.391465136	0.922756659	0.818893281
eda_min	0.696081	0.705033	0.85467	0.985221	0.981285	1.284494
eda_max	1.330437	0.790723	2.384584	2.241343	4.738588	4.140133
temp_mean	34.211019	35.50671062	34.79859016	34.3760053	34.24123841	32.87140204
temp_std	0.3252817	0.161047078	0.313185504	0.424502451	0.5510138	0.333745668
temp_min	33.68	34.97	34.45	33.71	33.57	32.41
temp_max	34.97	35.71	35.49	35.27	35.31	33.61

Table 19: EDA and Temperature features for S5

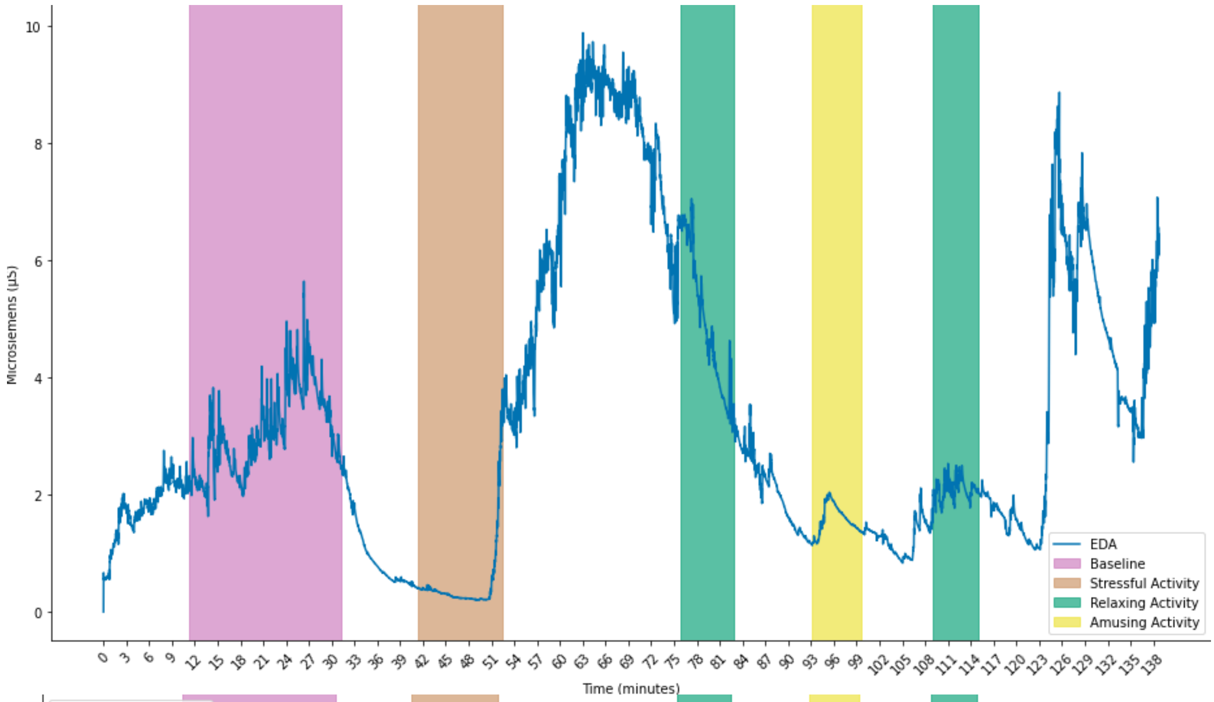
HRV Features for S5:

Extracted_Features	S5_Neutral	S5_Amused	S5_Stressed
HRV_MeanNN	985.7486264	1071.828358	2797.883065
HRV_SDNN	528.0839071	487.4487454	2521.771264
HRV_SDANN1	170.5011406	77.61536153	725.3852613
HRV_RMSSD	639.6878434	575.432591	3553.670047
HRV_pNN50	82.69230769	55.52238806	95.96774194
HRV_LF	0.021439384	0.01213352	0.018269231
HRV_HF	0.008332316	0.011018393	0.001260141
HRV_LFHF	2.573040256	1.101205969	14.49776616

Table 20: HRV features for S5

Subject 6 (S6)

EDA Visualization for S6:



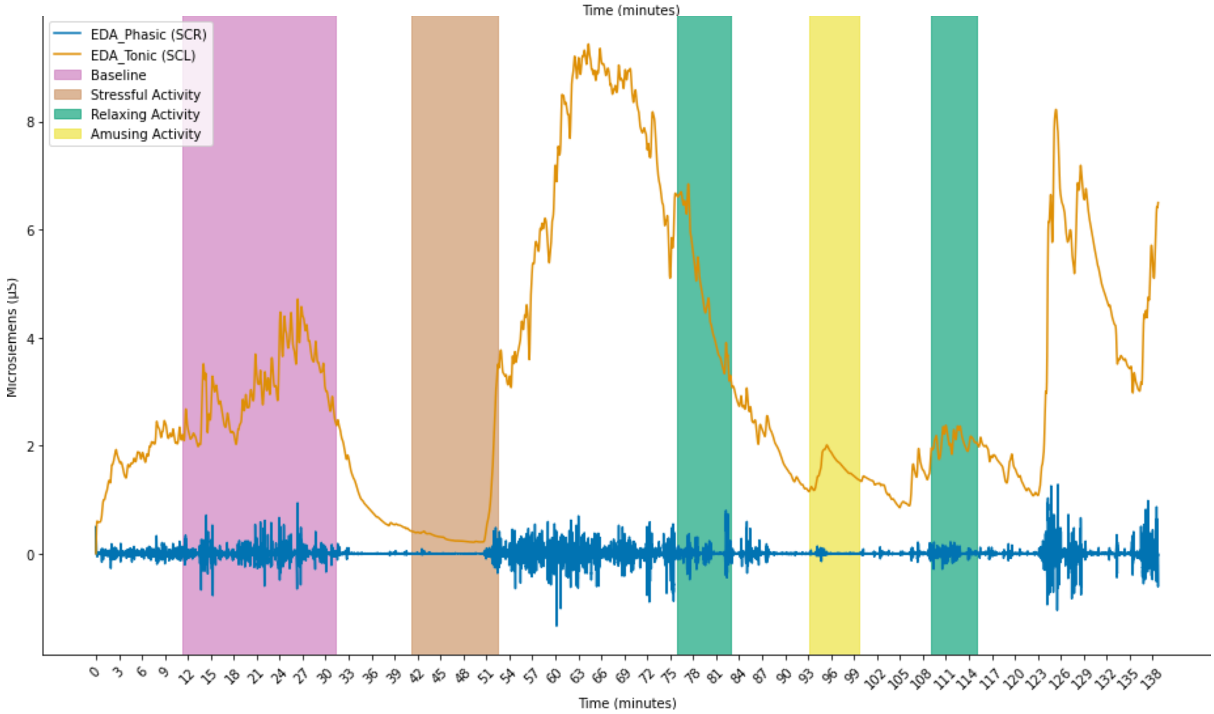


Figure 17: EDA visualization for S6: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S6:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	0.9998792	0.454606853	7.011504755	4.913355873	1.577574285	2.091170579
eda_std	0.5996097	0.551240106	1.973392124	1.161406967	0.244078931	0.174243435
eda_min	0.4102758	0.20278188	2.801172016	3.064389058	1.132869246	1.623633488
eda_max	2.6539832	3.519859137	9.875940013	7.046208603	2.040102124	2.530771429
temp_mean	32.746562	34.02529653	33.09626044	31.47309167	30.77695985	32.30446218
temp_std	0.7784157	0.117648839	0.705629545	0.166690636	0.154611292	0.128495831
temp_min	31.45	33.81	31.71	31.23	30.41	31.95
temp_max	33.93	34.29	34.21	31.75	30.97	32.45

Table 21: EDA and Temperature features for S6

HRV Features for S6:

Extracted_Features	S6_Neutral	S6_Stressed	S6_Amused
HRV_MeanNN	886.3425926	879.5955882	910.2056962
HRV_SDNN	206.4749259	244.7632604	216.1206123
HRV_SDANN1	29.08907116	48.02062347	11.82550766
HRV_RMSSD	291.460899	344.7902091	321.5457911
HRV_pNN50	64.9382716	68.1372549	66.58227848
HRV_LF	0.030413988	0.059488246	0.012375486
HRV_HF	0.078962179	0.098085685	0.058082074
HRV_LFHF	0.385171591	0.606492642	0.213068938

Table 22: HRV features for S6

Subject 7 (S7)

EDA Visualization for S7:

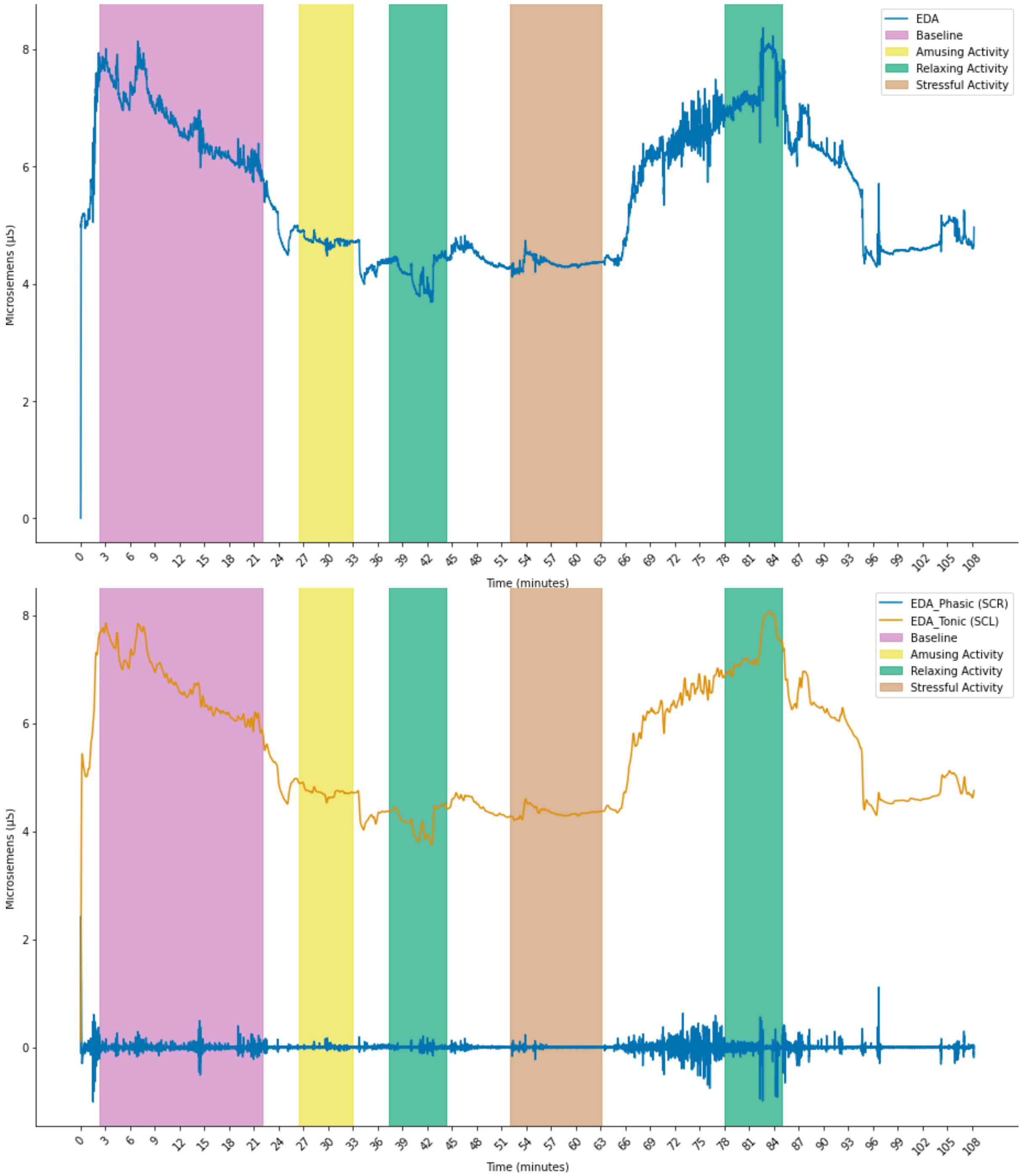


Figure 18: EDA visualization for S7: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S7:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	5.0553206	4.72811748	4.186324974	4.346560577	5.9427414	7.369754393
eda_std	0.3591042	0.081239986	0.239940838	0.080525103	0.872901161	0.408064749
eda_min	4.4843471	4.477397865	3.685903561	4.112274957	4.303982571	6.40419448
eda_max	5.8235147	4.916827616	4.561433118	4.737129518	7.487214617	8.362132313
temp_mean	33.43146	34.11509242	33.98665668	33.34112457	33.36049875	32.65321237
temp_std	0.3850957	0.242877654	0.294115387	0.466621896	0.406716804	0.065387024
temp_min	32.95	33.73	33.47	32.93	32.81	32.53
temp_max	34.11	34.59	34.43	34.61	34.47	32.83

Table 23: EDA and Temperature features for S7

HRV Features for S7:

Extracted_Features	S7_Neutral	S7_Amused	S7_Stressed
HRV_MeanNN	833.2729118	850.8960308	981.8135246
HRV_SDNN	177.3814291	213.0921426	162.8613358
HRV_SDANN1	27.86588904	42.3983986	39.8045985
HRV_RMSSD	217.7601671	282.351983	151.390618
HRV_pNN50	51.74013921	59.71563981	55.46448087
HRV_LF	0.032400153	0.023099219	0.026430103
HRV_HF	0.047232621	0.064961643	0.013857098
HRV_LFHF	0.685969815	0.355582432	1.907333144

Table 24: HRV features for S7

Subject 8 (S8)

EDA Visualization for S8:

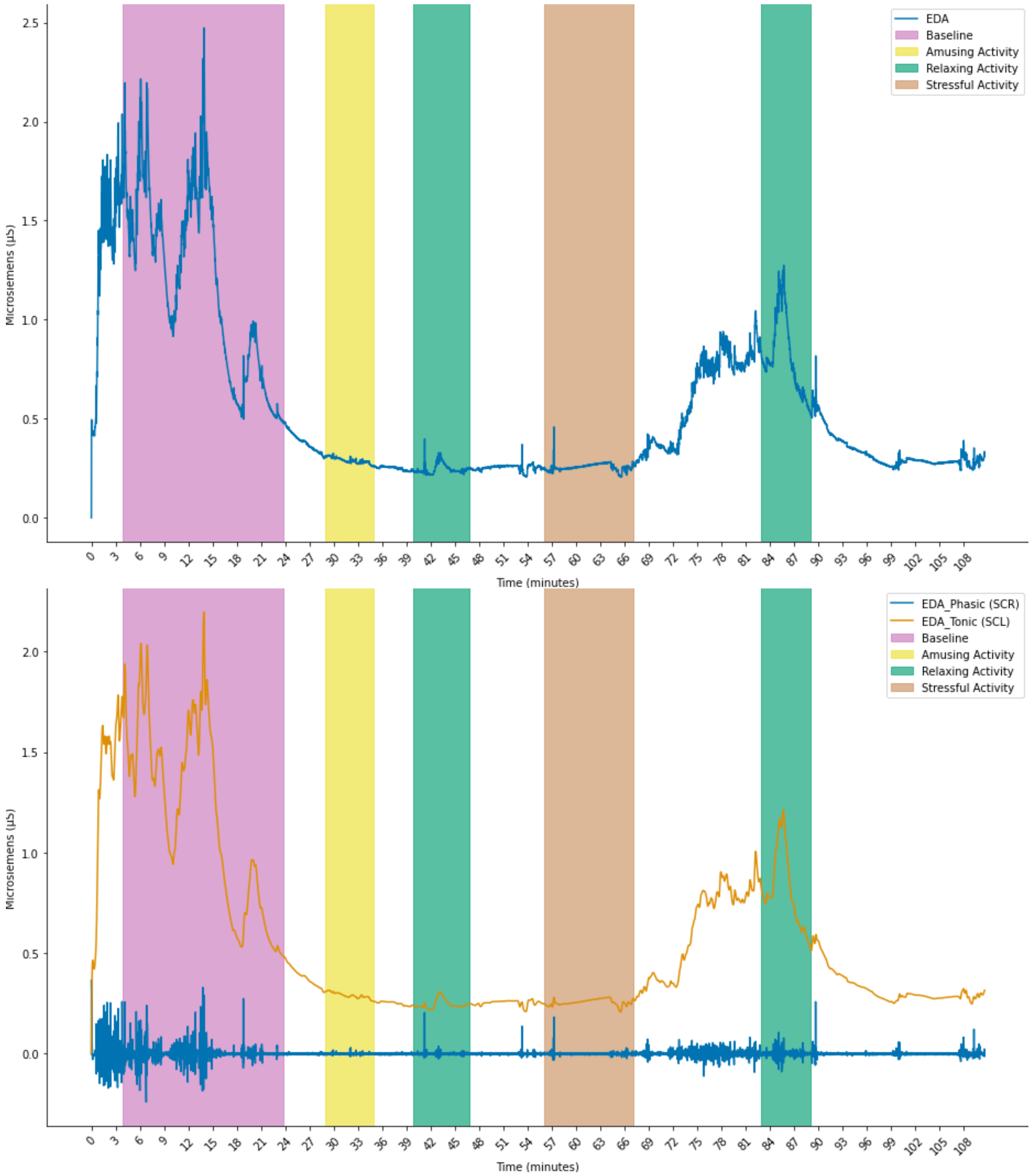


Figure 19: EDA visualization for S8: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S8:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	0.3841185	0.289286978	0.245446847	0.254599553	0.601342446	0.81643192
eda_std	0.0490878	0.014165752	0.023514279	0.017198165	0.222392351	0.193765411
eda_min	0.2976718	0.259032044	0.214982261	0.206643338	0.25809112	0.520294992
eda_max	0.4865491	0.324421455	0.397235832	0.458375356	1.045223853	1.274774611
temp_mean	33.675395	33.75208883	33.58482451	33.22788918	32.62917743	32.23045791
temp_std	0.0566132	0.045977793	0.026460585	0.077522365	0.264733242	0.11595218
temp_min	33.53	33.65	33.5	32.95	31.99	32.03
temp_max	33.77	33.81	33.63	33.31	32.97	32.41

Table 25: EDA and Temperature features for S8

HRV Features for S8:

Extracted_Features	S8_Neutral	S8_Amused	S8_Stressed
HRV_MeanNN	862.9432091	855.2083333	858.5526316
HRV_SDNN	164.1584904	465.4994528	243.0063371
HRV_SDANN1	22.6773247	55.71734135	31.61443134
HRV_RMSSD	213.5846697	655.856549	288.6112416
HRV_pNN50	53.84615385	63.80952381	69.37799043
HRV_LF	0.025781838	0.032616441	0.025372235
HRV_HF	0.060279425	0.000862407	0.018065486
HRV_LFHF	0.427705439	37.82024511	1.404459035

Table 26: HRV features for S8

Subject 9 (S9)

EDA Visualization for S9:

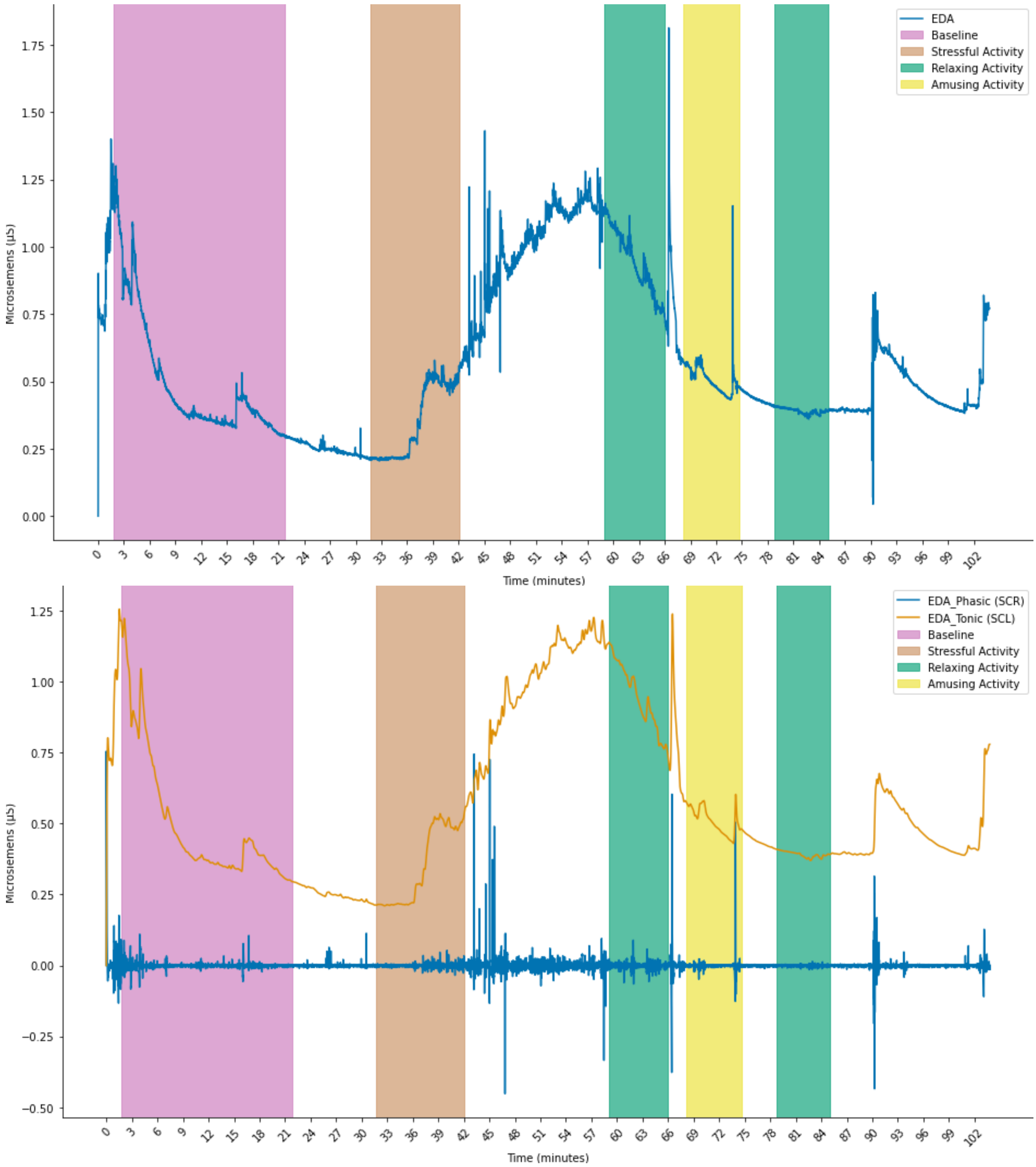


Figure 20: EDA visualization for S9: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S9:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	0.2506024	0.348648448	0.981242804	0.946466969	0.508551382	0.391053926
eda_std	0.0230246	0.134336741	0.191184397	0.114109612	0.055211048	0.010659189
eda_min	0.2073737	0.204458912	0.523973605	0.744200689	0.43200632	0.360252705
eda_max	0.3269401	0.578804995	1.431007023	1.16198538	1.152095634	0.410805347
temp_mean	33.927581	34.59605401	33.38401184	32.5100119	31.47817081	31.1617996
temp_std	0.3927722	0.116974263	0.508694688	0.145686338	0.349681135	0.045550808
temp_min	33.27	34.37	32.65	32.18	30.97	31.07
temp_max	34.47	34.79	34.39	32.71	32.07	31.25

Table 27: EDA and Temperature features for S9

HRV Features for S9:

Extracted_Features	S9_Neutral	S9_Stressed	S9_Amused
HRV_MeanNN	810.736456	799.6651786	844.2634977
HRV_SDNN	240.2754132	253.7876721	357.6690166
HRV_SDANN1	43.81311462	27.04556246	76.71859752
HRV_RMSSD	317.5079496	345.8701713	465.8180364
HRV_pNN50	63.43115124	60.04464286	63.14553991
HRV_LF	0.04950317	0.033932926	0.032315967
HRV_HF	0.062412344	0.078348521	0.007825252
HRV_LFHF	0.793163126	0.433102313	4.129703246

Table 28: HRV features for S9

Subject 10 (S10)

EDA Visualization for S10:

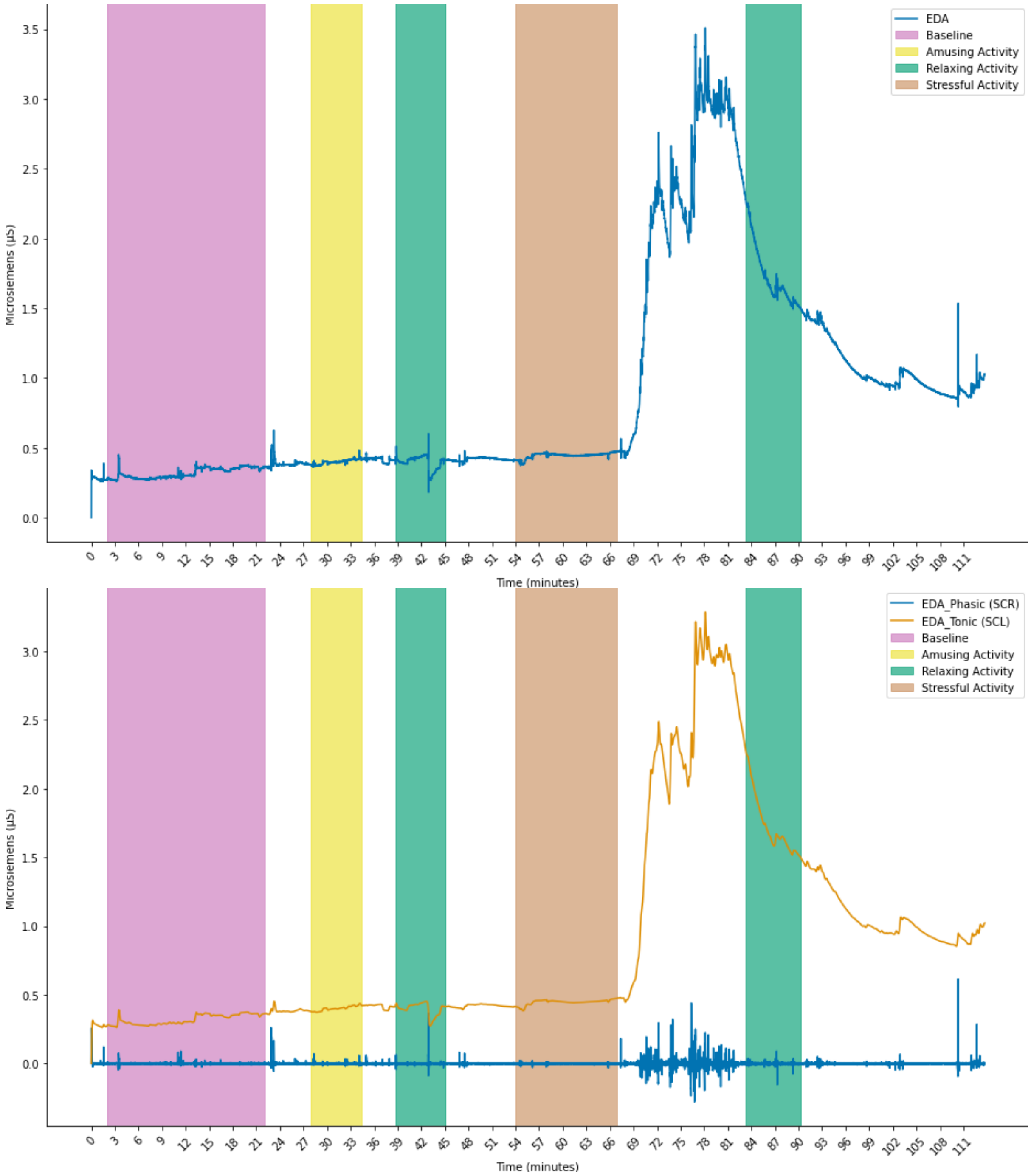


Figure 21: EDA visualization for S10: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S10:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	0.3828844	0.399660046	0.396349805	0.446193128	2.132589957	1.737692519
eda_std	0.0205763	0.017214574	0.04895368	0.01843341	0.867130818	0.212661245
eda_min	0.3370397	0.362802183	0.181845255	0.373124692	0.424864066	1.493804962
eda_max	0.6268472	0.483706374	0.602186428	0.475843082	3.509852909	2.281218844
temp_mean	33.326549	33.61842575	34.09913015	34.38548721	34.01614639	32.9740526
temp_std	0.0608715	0.090469393	0.084054169	0.107986504	0.516256282	0.05489175
temp_min	33.16	33.41	33.99	34.21	33.09	32.89
temp_max	33.45	33.87	34.29	34.63	34.71	33.13

Table 29: EDA and Temperature features for S10

HRV Features for S10:

Extracted_Features	S10_Neutral	S10_Amused	S10_Stressed
HRV_MeanNN	728.4286437	720.5070281	779.3180586
HRV_SDNN	374.0019399	480.0489454	140.2394176
HRV_SDANN1	118.9995917	109.1504186	32.14073738
HRV_RMSSD	413.5327865	632.5313335	161.3995189
HRV_pNN50	37.24696356	43.37349398	33.40563991
HRV_LF	0.006858283	0.030285378	0.037976317
HRV_HF	0.011092464	0.001719183	0.033275627
HRV_LFHF	0.61828314	17.61614406	1.141265266

Table 30: HRV features for S10

Subject 11 (S11)

EDA Visualization for S11:

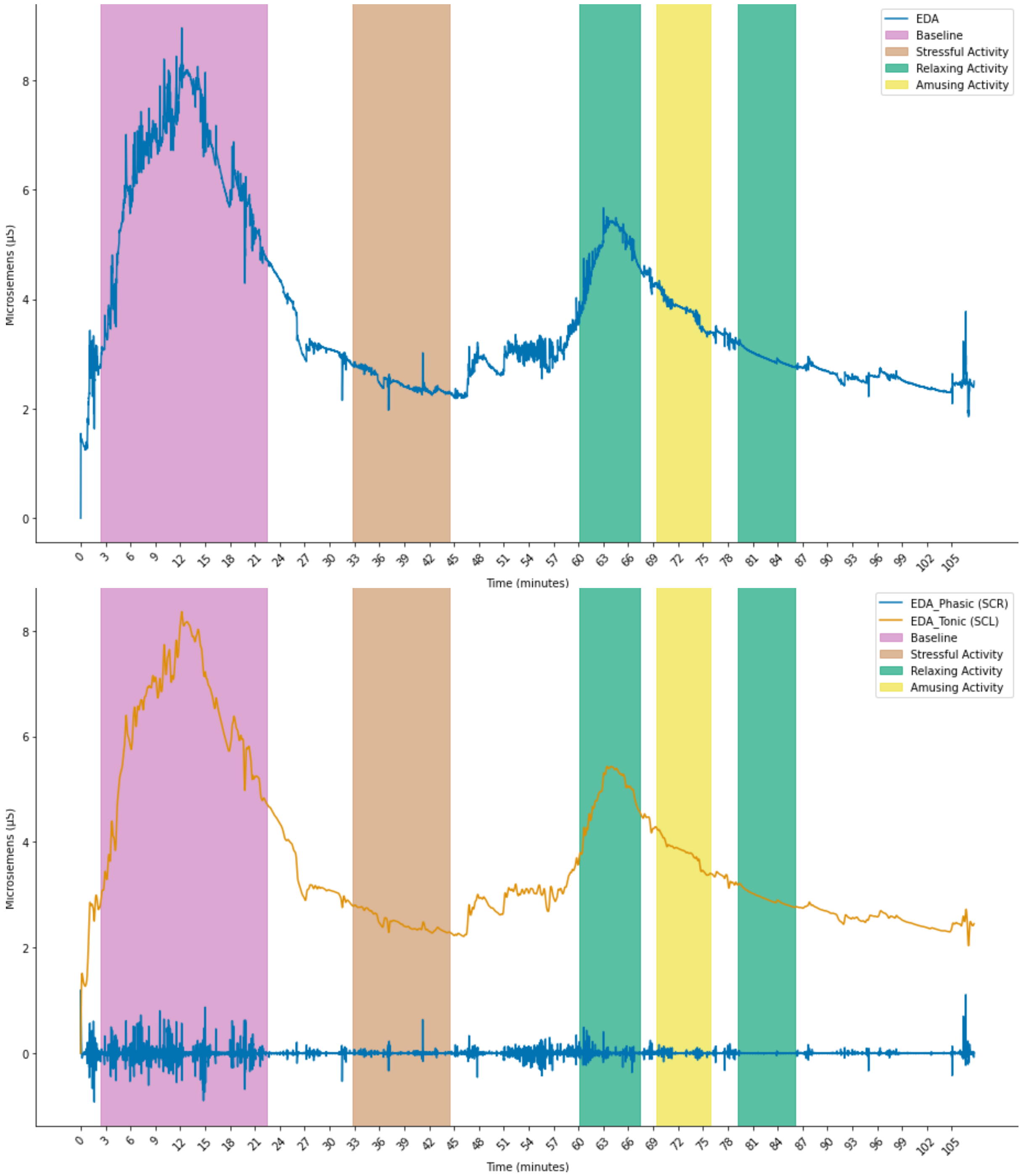


Figure 22: EDA visualization for S11: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S11:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	3.4778684	2.479751468	2.895547335	4.886637432	3.799062187	2.945831097
eda_std	0.6141904	0.168268963	0.343947827	0.480014137	0.237311764	0.124723612
eda_min	2.1537483	1.97433466	2.187653579	3.583110148	3.311849578	2.753261272
eda_max	4.7321701	3.022469826	4.030156455	5.671806046	4.343137932	3.264419503
temp_mean	34.194933	34.38178151	33.63093992	32.52128321	31.84303284	31.54632432
temp_std	0.0967393	0.032479419	0.482630169	0.115648409	0.22554251	0.026284478
temp_min	34.05	34.29	32.75	32.27	31.51	31.47
temp_max	34.34	34.47	34.41	32.79	32.21	31.61

Table 31: EDA and Temperature features for S11

HRV Features for S11:

Extracted_Features	S11_Neutral	S11_Stressed	S11_Amused
HRV_MeanNN	819.0133827	818.7071918	766.4245736
HRV_SDNN	164.220772	215.7811736	403.6456859
HRV_SDANN1	22.37857638	39.63891231	77.27811731
HRV_RMSSD	234.9699925	299.4700205	547.8585478
HRV_pNN50	62.64236902	71.68949772	60.76759062
HRV_LF	0.037361685	0.029157671	0.007306552
HRV_HF	0.083831156	0.061073785	0.004313612
HRV_LFHF	0.445677793	0.477417128	1.693836235

Table 32: HRV features for S11

Subject 13 (S13)

EDA Visualization for S13:

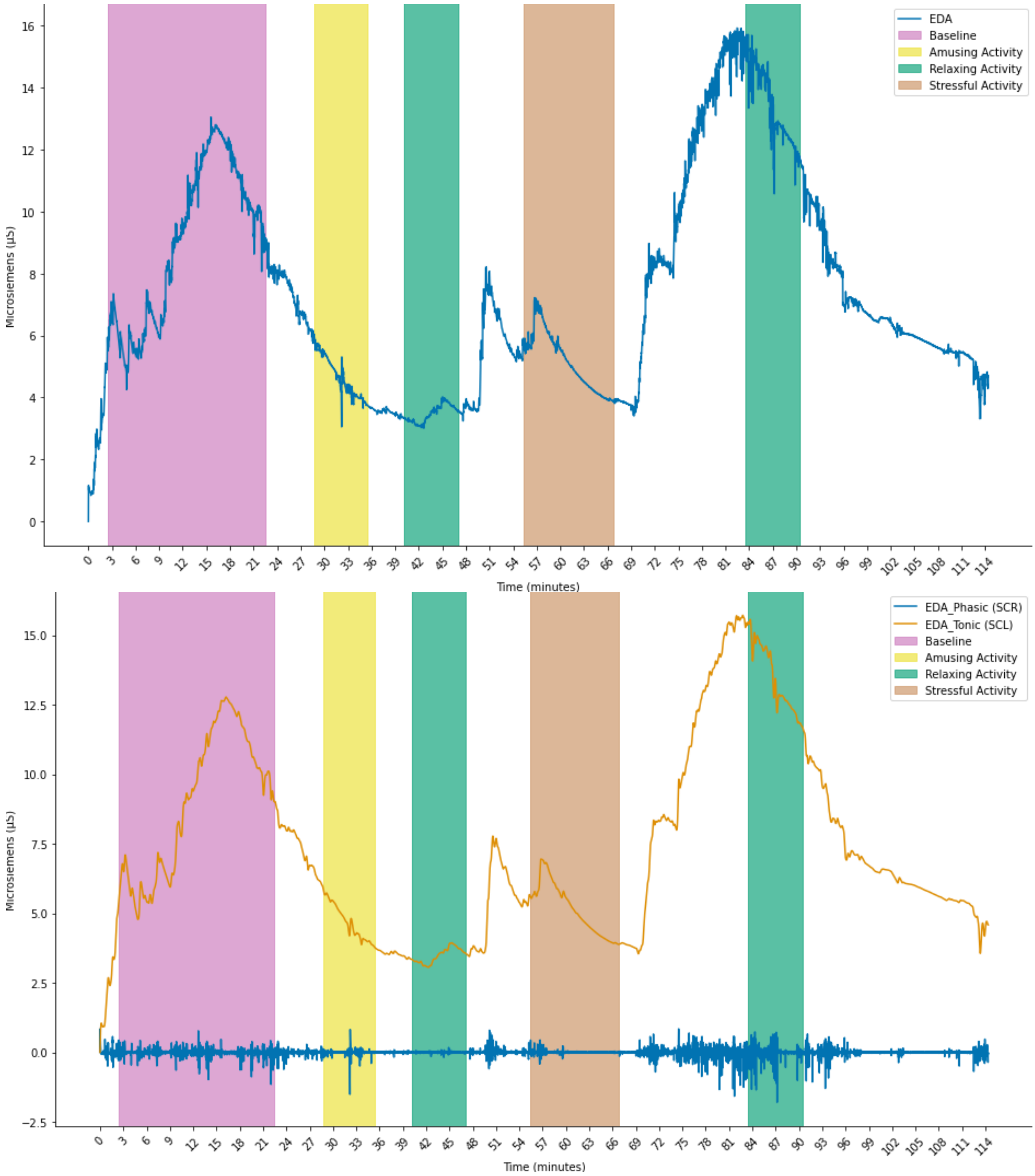


Figure 23: EDA visualization for S13: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S13:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	7.4110559	4.670375738	3.477049401	5.156471257	10.04264275	13.47057437
eda_std	0.8219805	0.640546062	0.273024539	0.915084001	4.166324954	1.189307029
eda_min	5.7525152	3.054423122	3.009131093	3.879148603	3.407215602	10.57955459
eda_max	9.1540459	5.944766973	4.021848146	7.221322374	15.93144442	15.72201391
temp_mean	34.744295	34.80543816	34.93864316	34.80064304	34.34975531	33.04020971
temp_std	0.0524209	0.045040663	0.05664573	0.062513625	0.588479867	0.066449937
temp_min	34.65	34.71	34.81	34.66	33.21	32.97
temp_max	34.83	34.89	35.03	34.95	34.99	33.25

Table 33: EDA and Temperature features for S13

HRV Features for S13:

Extracted_Features	S13_Neutral	S13_Amused	S13_Stressed
HRV_MeanNN	815.1278409	799.3055556	776.2784091
HRV_SDNN	318.6080482	359.0102602	98.78426551
HRV_SDANN1	61.20323138	74.52167962	19.74635892
HRV_RMSSD	401.0087694	489.7408932	73.04526866
HRV_pNN50	65	62.88888889	28.35497835
HRV_LF	0.053119208	0.026873914	0.031198613
HRV_HF	0.021117212	0.01762449	0.009928962
HRV_LFHF	2.515446043	1.524805164	3.142182801

Table 34: HRV features for S13

Subject 14 (S14)

EDA Visualization for S14:

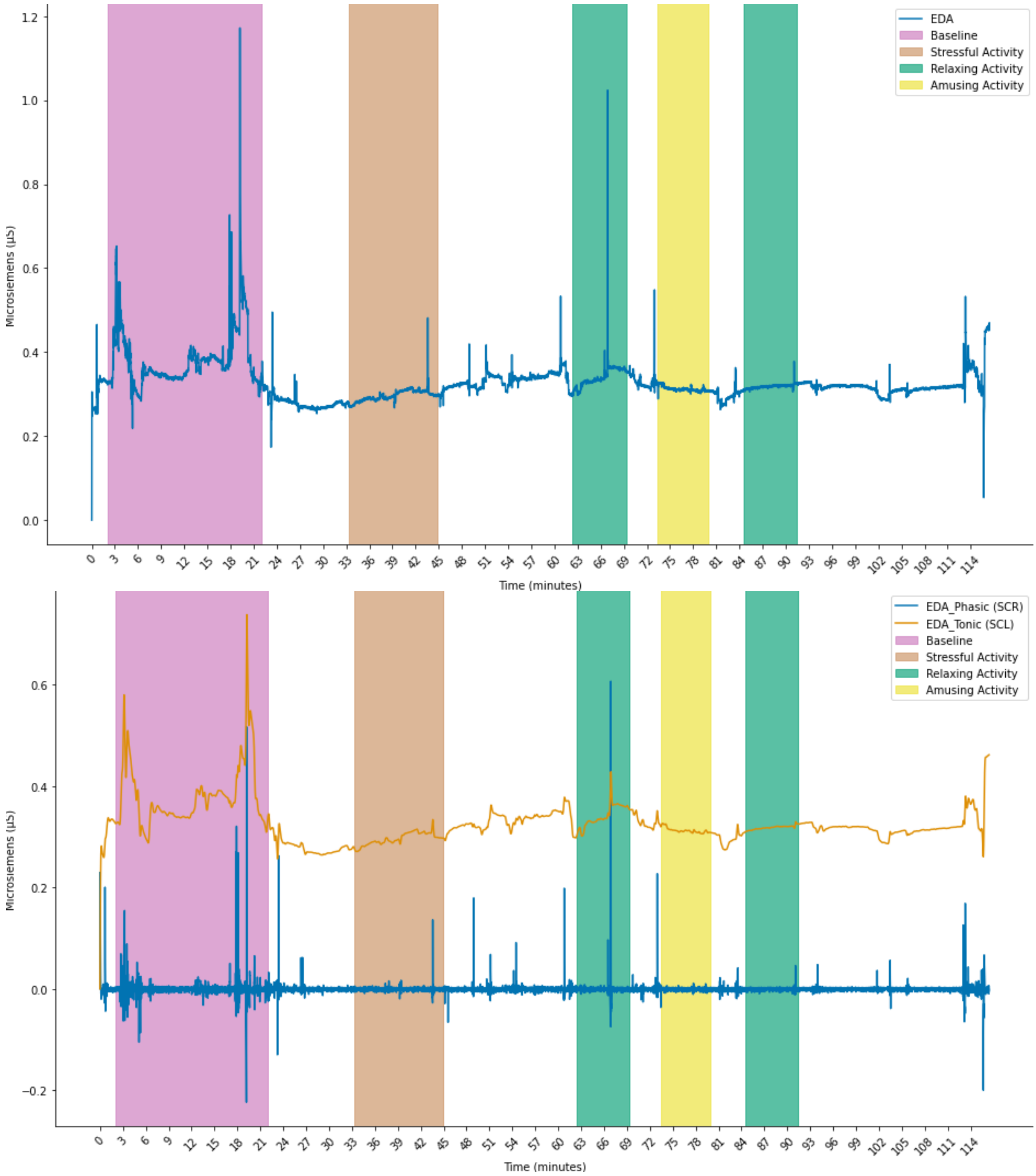


Figure 24: EDA visualization for S14: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S14:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	0.2806453	0.296247719	0.331928204	0.318026949	0.312554469	0.341142787
eda_std	0.0180256	0.013353388	0.01806537	0.004754395	0.005608957	0.033642886
eda_min	0.1737445	0.267373101	0.269667273	0.30510246	0.288820365	0.295835222
eda_max	0.4952406	0.481543084	0.533147893	0.377866181	0.329352419	1.023554631
temp_mean	32.149201	32.18839986	32.6300191	32.4622828	32.93294455	33.07591971
temp_std	0.1089827	0.065674875	0.158229339	0.068119492	0.124990748	0.082392015
temp_min	31.91	32.05	32.33	32.29	32.65	32.93
temp_max	32.31	32.39	32.99	32.57	33.07	33.23

Table 35: EDA and Temperature features for S14

HRV Features for S14:

Extracted_Features	S14_Neutral	S14_Stressed	S14_Amused
HRV_MeanNN	827.5849654	765.0253198	790.3502747
HRV_SDNN	135.9680065	184.382058	215.0392512
HRV_SDANN1	29.24246553	82.68981959	31.35987611
HRV_RMSSD	196.1231014	238.5030865	288.178883
HRV_pNN50	66.359447	59.2750533	69.01098901
HRV_LF	0.03302771	0.01534261	0.033011437
HRV_HF	0.079868451	0.029414225	0.036981955
HRV_LFHF	0.413526357	0.521605093	0.892636338

Table 36: HRV features for S14

Subject 15 (S15)

EDA Visualization for S15:

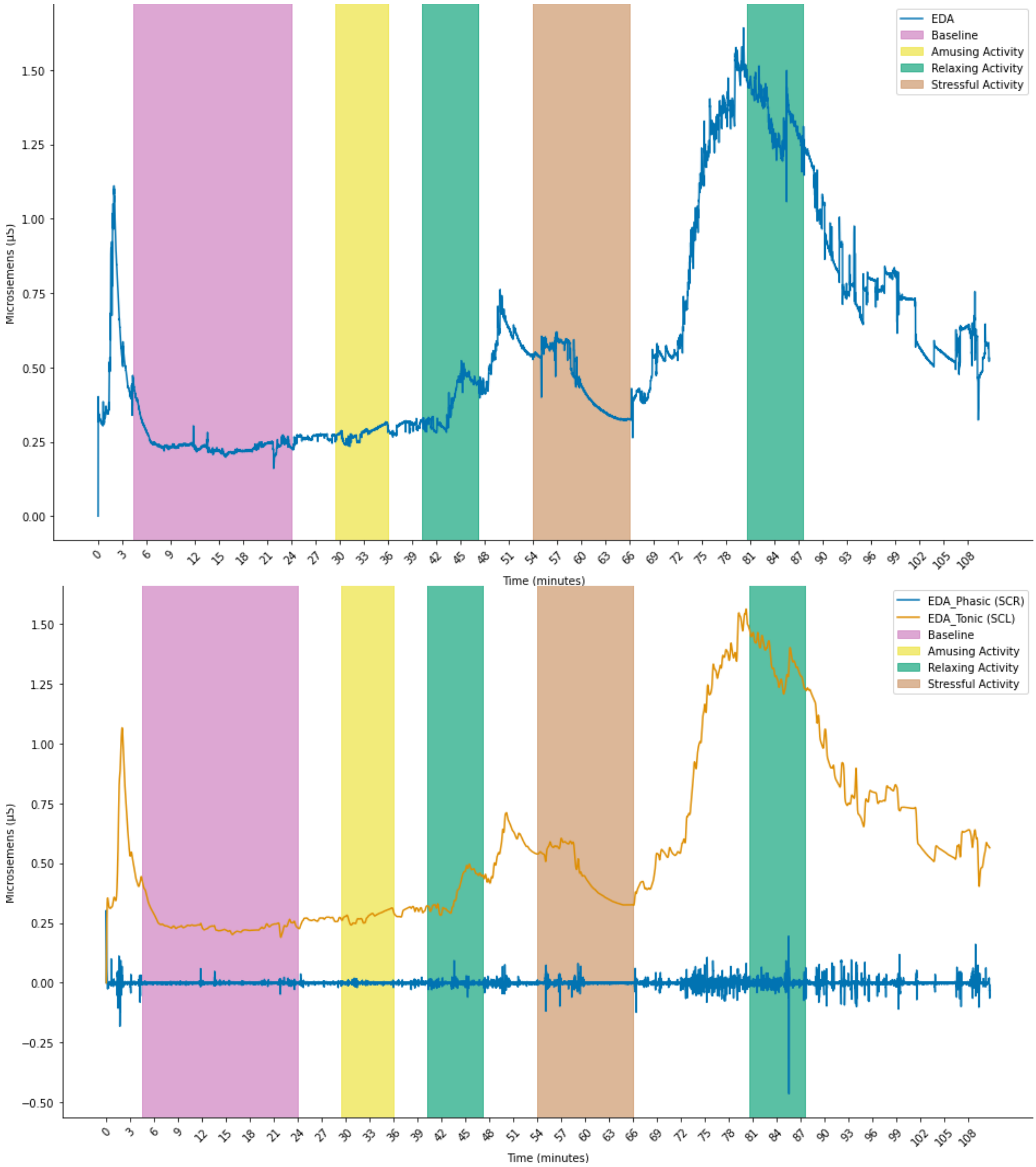


Figure 25: EDA visualization for S15: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S15:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	0.2635721	0.277511713	0.377944073	0.452705101	0.891466611	1.342173556
eda_std	0.0111968	0.020276933	0.075021187	0.102987856	0.416612018	0.079281777
eda_min	0.2230736	0.234296095	0.281100851	0.321246274	0.263536407	1.057610214
eda_max	0.2776129	0.317255389	0.522902473	0.619845091	1.642359471	1.514220425
temp_mean	29.857742	29.97717655	30.31812463	29.96219715	30.14578887	30.04499101
temp_std	0.0847976	0.161606798	0.074336007	0.267913242	0.062954921	0.053060469
temp_min	29.59	29.65	30.21	29.37	30.01	29.93
temp_max	29.95	30.23	30.45	30.23	30.33	30.15

Table 37: EDA and Temperature features for S15

HRV Features for S15:

Extracted_Features	S15_Neutral	S15_Amused	S15_Stressed
HRV_MeanNN	1151.764113	953.9145612	901.3549499
HRV_SDNN	1296.444947	932.9221704	285.5463818
HRV_SDANN1	305.4087269	141.2051415	114.6290603
HRV_RMSSD	1666.713519	1305.167015	381.4950634
HRV_pNN50	80.32258065	73.67021277	38.34586466
HRV_LF	0.00427401	0.010891882	0.008389735
HRV_HF	0.000430326	0.000258525	0.009360293
HRV_LFHF	9.93203727	42.13093007	0.896311156

Table 38: HRV features for S15

Subject 16 (S16)

EDA Visualization for S16:

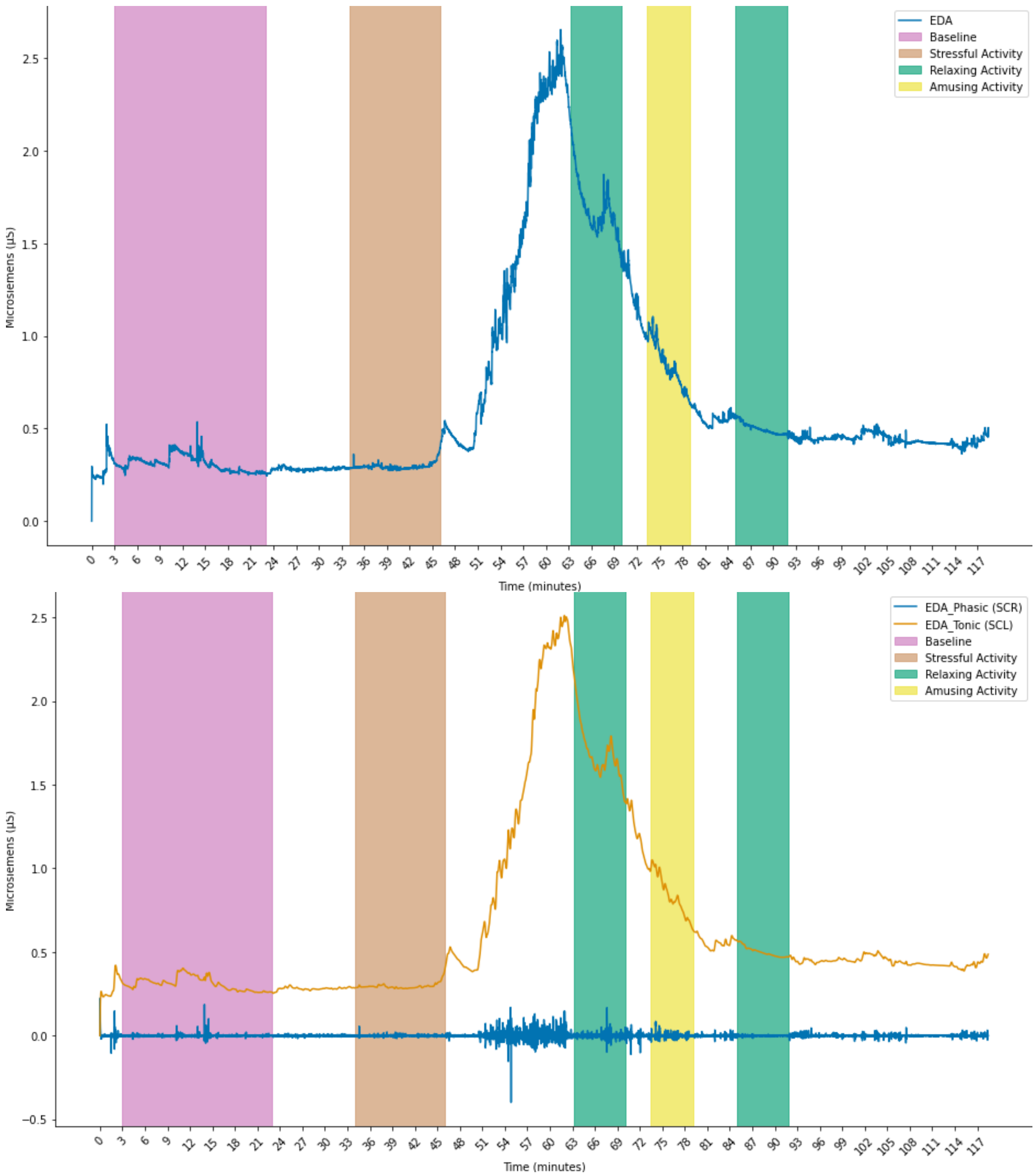


Figure 26: EDA visualization for S16: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S16:

Features	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
eda_mean	0.2806009	0.295514656	1.307337715	1.692310293	0.840071564	0.500902757
eda_std	0.0087797	0.017968304	0.775782368	0.153866822	0.118061619	0.029809796
eda_min	0.2443231	0.272184948	0.377377266	1.378539779	0.630701737	0.464510853
eda_max	0.3050066	0.398720005	2.654885955	2.149891315	1.105013965	0.578326329
temp_mean	29.570159	30.75506074	31.04900024	30.69912	30.92793154	30.41908328
temp_std	0.2511369	0.227939638	0.082596602	0.080782487	0.152372176	0.132592479
temp_min	29.33	30.27	30.83	30.53	30.57	30.19
temp_max	30.31	31.09	31.19	30.87	31.17	30.65

Table 39: EDA and Temperature features for S16

HRV Features for S16:

Extracted_Features	S16_Neutral	S16_Stressed	S16_Amused
HRV_MeanNN	933.2792208	882.409398	817.4473235
HRV_SDNN	259.2436633	257.2029889	288.442358
HRV_SDANN1	41.52261284	85.40375414	32.60329641
HRV_RMSSD	334.1594631	342.3617287	409.3717866
HRV_pNN50	76.62337662	70.27027027	77.44874715
HRV_LF	0.026265176	0.043585445	0.027859413
HRV_HF	0.05716757	0.086604474	0.06986148
HRV_LFHF	0.45944188	0.503270132	0.398780743

Table 40: HRV features for S16

Subject 17 (S17)

EDA Visualization for S17:

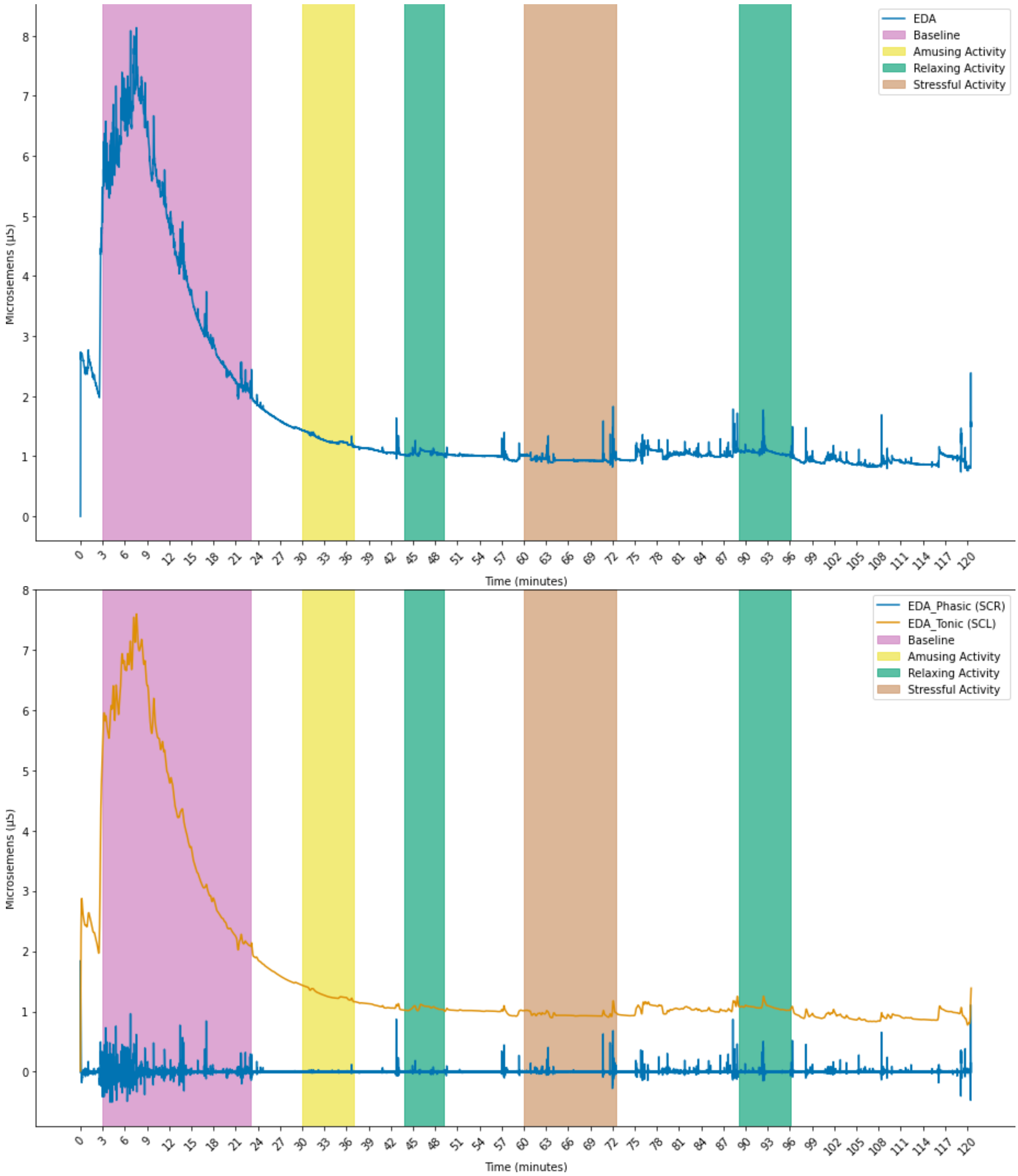


Figure 27: EDA visualization for S17: Unified signal (upper), decomposed signal (lower)

EDA and Temperature Features for S17:

Features	Neutral	Amusing Activity	Relaxed 1	Stressful Activity	Post_Stress	Relaxed 2
eda_mean	1.6552717	1.2790937	1.058047465	0.949016981	1.032340942	1.070655454
eda_std	0.1684359	0.073315932	0.032239713	0.054222441	0.074247091	0.052438441
eda_min	1.4291044	1.157640018	1.005312864	0.820302838	0.87851814	1.008199128
eda_max	2.4446253	1.435577316	1.265447954	1.829728351	1.785362665	1.771172155
temp_mean	33.446952	33.44449016	33.00053643	32.54559368	32.27753305	32.66283042
temp_std	0.0285121	0.052167618	0.095790256	0.070871461	0.170524188	0.235444117
temp_min	33.37	33.27	32.79	32.37	32.03	32.05
temp_max	33.5	33.53	33.15	32.68	32.66	32.91

Table 41: EDA and Temperature features for S17

HRV Features for S17:

Extracted_Features	S17_Neutral	S17_Amused	S17_Stressed
HRV_MeanNN	933.9285714	946.98219	919.1975703
HRV_SDNN	149.5722409	228.4276591	288.5054178
HRV_SDANN1	20.61940111	47.13094128	69.06922279
HRV_RMSSD	209.1136307	300.2389646	367.9874844
HRV_pNN50	76.62337662	82.58575198	76.98209719
HRV_LF	0.023345621	0.030513403	0.043652689
HRV_HF	0.060244599	0.075269834	0.019035888
HRV_LFHF	0.387513921	0.405386875	2.293178532

Table 42: HRV features for S17

Table for LF/HF power ratio for all participants. The values highlighted in blue are highest LF/HF ratio values for every individual across their different affective states.

Participant	Neutral	Stressed	Amused
S2	1.510593266	0.390587978	2.765667867
S3	0.575394286	4.352645349	13.28612573
S4	3.35379574	0.225093028	0.267406717
S5	2.573040256	1.101205969	14.49776616
S6	0.385171591	0.606492642	0.213068938
S7	0.685969815	0.355582432	1.907333144
S8	0.427705439	37.82024511	1.404459035
S9	0.793163126	0.433102313	4.129703246
S10	0.61828314	17.61614406	1.141265266
S11	0.445677793	0.477417128	1.693836235
S13	2.515446043	1.524805164	3.142182801
S14	0.413526357	0.521605093	0.892636338
S15	9.93203727	42.13093007	0.896311156
S16	0.45944188	0.503270132	0.398780743
S17	0.387513921	0.405386875	2.293178532

Table 43: LF/HF power ratio for all participants.

Table of all eda_mean values for every participant. The values highlighted in blue are the highest eda_mean for that participant across their individual affective states. Similarly, the values highlighted in green are lowest eda_mean for that participant across their individual affective states.

Participant	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
S2	0.698104251	0.114234257	0.44516844	0.980755548	0.452889623	0.209086095
S3	1.6339823	0.445804828	1.669038445	0.697514743	0.449593742	0.374245291
S4	0.3131825	0.139323958	0.158218885	0.146881342	1.202008897	1.113279311
S5	0.9365627	0.767052864	1.730517996	1.512306042	2.906584481	2.66331054
S6	0.9998792	0.454606853	7.011504755	4.913355873	1.577574285	2.091170579
S7	5.0553206	4.72811748	4.186324974	4.346560577	5.9427414	7.369754393
S8	0.3841185	0.289286978	0.245446847	0.254599553	0.601342446	0.81643192
S9	0.2506024	0.348648448	0.981242804	0.946466969	0.508551382	0.391053926
S10	0.3828844	0.399660046	0.396349805	0.446193128	2.132589957	1.737692519
S11	3.4778684	2.479751468	2.895547335	4.886637432	3.799062187	2.945831097
S13	7.4110559	4.670375738	3.477049401	5.156471257	10.04264275	13.47057437
S14	0.2806453	0.296247719	0.331928204	0.318026949	0.312554469	0.341142787
S15	0.2635721	0.277511713	0.377944073	0.452705101	0.891466611	1.342173556
S16	0.2806009	0.295514656	1.307337715	1.692310293	0.840071564	0.500902757
S17	1.6552717	1.2790937	1.058047465	0.949016981	1.032340942	1.070655454

Table 44: Table of mean EDA values for all participants.

Table contains temp_mean values for every participant across different affective states. The values highlighted in blue are the highest temp_mean for that participant across their individual affective states. Similarly, the values highlighted in green are lowest temp_mean for that participant across their individual affective states.

Participant	Neutral	Stressful Activity	Post_Stress	Relaxed 1	Amusing Activity	Relaxed 2
S2	35.7740312	35.75918619	34.59663784	32.66927906	33.06924133	34.29040906
S3	33.01025	33.20402878	32.31627134	31.43723593	30.75059957	30.69488387
S4	32.624813	32.9250733	33.04270172	32.86740438	32.61599822	32.1095541
S5	34.211019	35.50671062	34.79859016	34.3760053	34.24123841	32.87140204
S6	32.746562	34.02529653	33.09626044	31.47309167	30.77695985	32.30446218
S7	33.43146	34.11509242	33.98665668	33.34112457	33.36049875	32.65321237
S8	33.675395	33.75208883	33.58482451	33.22788918	32.62917743	32.23045791
S9	33.927581	34.59605401	33.38401184	32.5100119	31.47817081	31.1617996
S10	33.326549	33.61842575	34.09913015	34.38548721	34.01614639	32.9740526
S11	34.194933	34.38178151	33.63093992	32.52128321	31.84303284	31.54632432
S13	34.744295	34.80543816	34.93864316	34.80064304	34.34975531	33.04020971
S14	32.149201	32.18839986	32.6300191	32.4622828	32.93294455	33.07591971
S15	29.857742	29.97717655	30.31812463	29.96219715	30.14578887	30.04499101
S16	29.570159	30.75506074	31.04900024	30.69912	30.92793154	30.41908328
S17	33.446952	33.44449016	33.00053643	32.54559368	32.27753305	32.66283042

Table 45: Table of mean temperature values for all participants.

Appendix C: Supplementary information for Chapter IV

Pick-A-Mood scale modified to be used in this research. Cartoons collected from original authors [21].

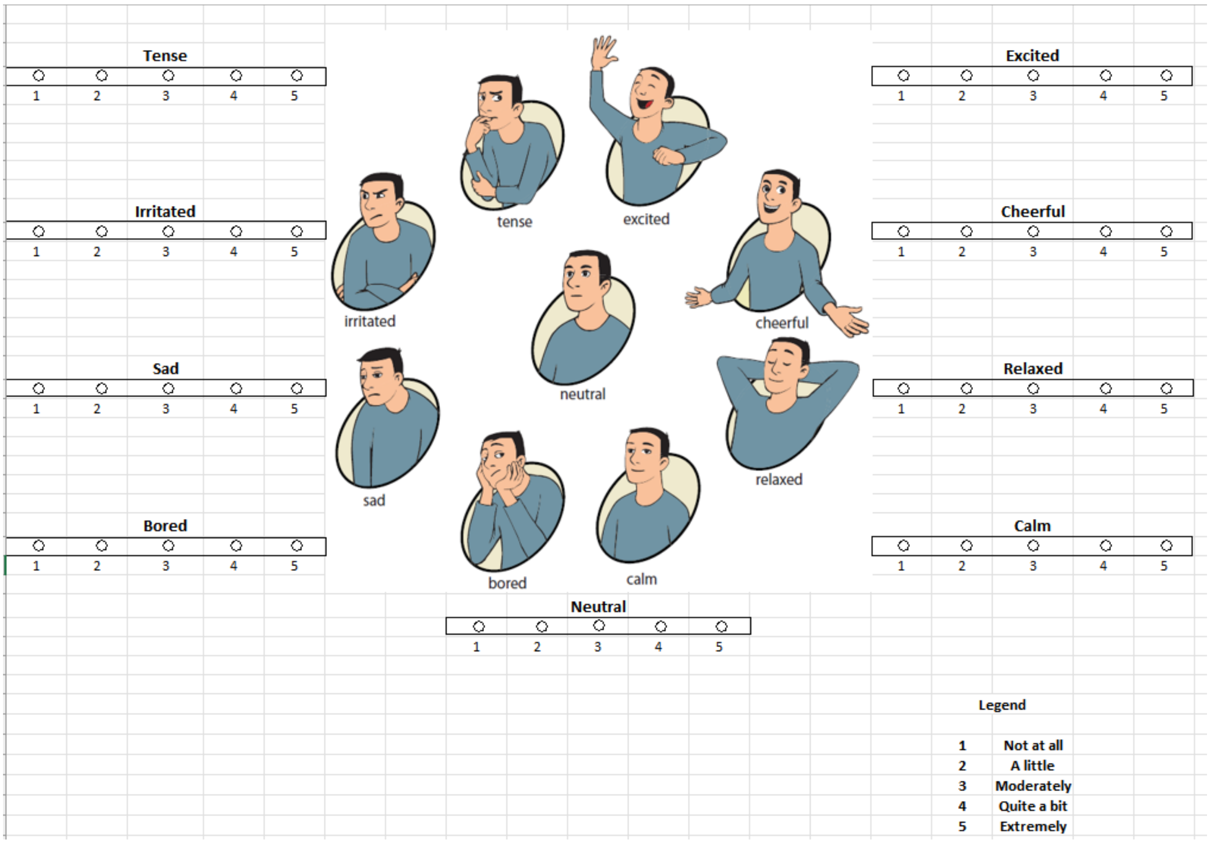


Figure 28: Modified Pick-A-Mood scale with male characters

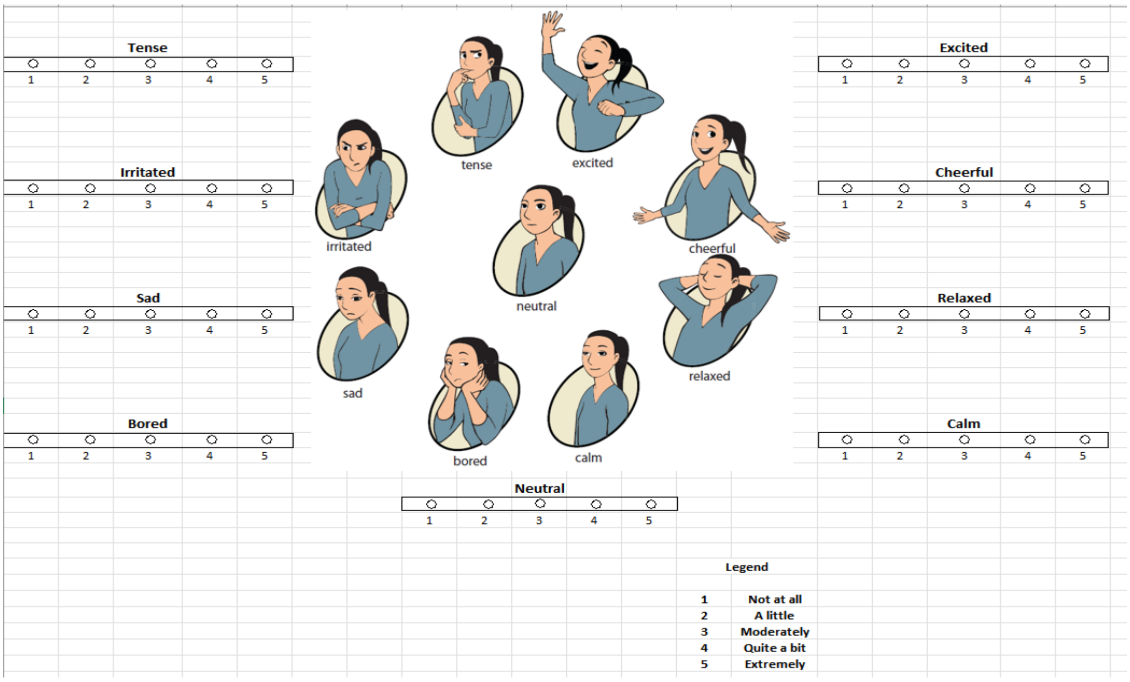


Figure 29: Modified Pick-A-Mood scale with female characters

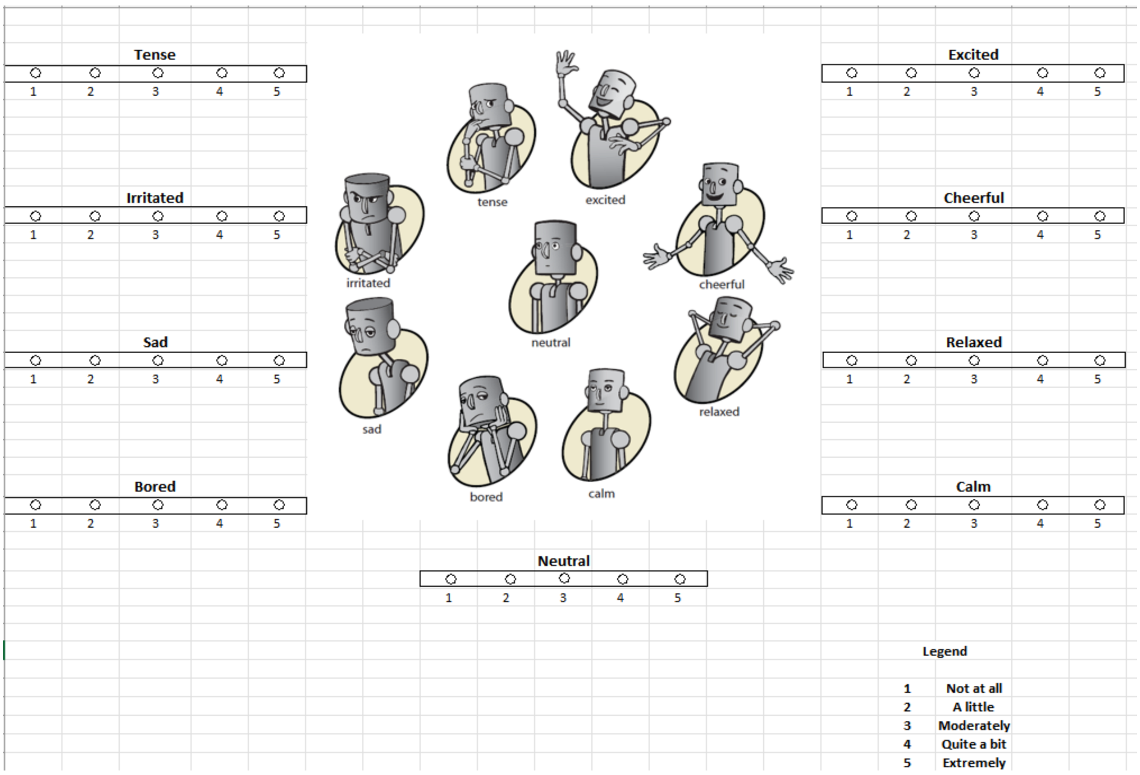


Figure 30: Modified Pick-A-Mood scale with robotic character

Appendix D: Analysis matrix for qualitative data

Initial Codes	Theme deduced	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Possess some kind of smart technological equipment (phone, laptop etc.). Excluding a basic phone		Yes, Smartphone	Yes, Phone, tablet, laptop, PS 3&4, Smartwatch	Uses smartphone for messaging, emails, pictures	Uses smartphone for contacting family and playing chess	Yes, possesses a smartphone, but uses iPads for social media	No. No smartphone, no computer. Only a small basic phone (just to dial 911).	No. Just has a regular telephone.	Yes. Use case "WhatsApp, Messenger, Email, Facebook, Telephone, Calendar, Banking." Also, computer games, Netflix, movies, TV sports.	Yes. Smartphone (communicating), computer (looking things up).	Yes. "Internet searches. Crossword. Scrabble. Google searches, Google Maps."	Smartphone for basic things. Never had a TV. But did bring a laptop during the interview (needed help with email).
	1. Possession with using technology (smartphones etc.)	Yes	Yes	Yes	Yes	Yes	No. Confirms that he is digitally disconnected.	Did not mention other technologies.	Yes	Yes, however "I'm not a digitally happy person".	Yes.	Yes
On being asked "how are you?" in a conversation OR On being asked if they are comfortable with sharing their daily affective state with strangers.	2. Genuinely express their feelings in a conversation	Depends on who is on the other side of conversation. "If somebody can't do anything about it, I probably wouldn't. "	Needs familiarity with the other person before expressing (in terms of affective state) himself to them.	Tries to put on a positive spin (best face), regardless of how they actually feel. "I'm aware that I can impact the way other people feel, and I don't want to bring people down"	Comfortable with sharing how they're feeling with other people, including random strangers.	Honestly expresses how she is feeling, regardless of familiarity with the person who is asking.	Mostly yes (even sadness). But the answer would depend on whether the closeness to the individual who is asking the question.	Does not elaborate, and usually gives the same "stock" answer, "I'm fine", **to everyone**.	"Always good". Does not matter who is asking, always honest response is given. "When it's bad, it's temporary and we can deal with that".	"I am fine", majority of the time, which is honest. BUT "To me, it's not an important part of my makeup, discussing how I feel with everybody". AND "It's not something that people with discuss with me, nor do I discuss it with them unless it is one of my other tenants that I've had been dealing with who had hospitalizations, and health problems. Then I will discuss things with them as to how they feel. But they don't, there's no discussion with them on my part as to how I'm feeling."	Honestly expresses with everyone.	Depends on who is asking. Honestly expresses with people who care and are compassionate.
Asked about their affective state (mood) specifically by anyone?	INCONCLUSIVE	No. A general how are you?		Expresses freely to the people who are closest to P3.	Keeps in touch with family.					None. "But I grew up in a family that did not express a whole lot of, we didn't discuss our moods, we just got on with our day and that was it." Usually it's "the other way around". (due to experience as a nurse.		Nurses, PSW's
Frequency of such interactions	2. Time span between conversations involving feelings.	Couple of times a day	Once a week.	Every day.	Quite often. Visits, calls.		Other than just greeting people (3-4 times a day),	Tries to interact with people daily,	Daily interactions.		Rarely if specific to mood. Otherwise,	3-4 times a day

	COMBINED WITH 2.						son calls once a month.	“however casually”.			generally asked often “how are you?”	
Daily communication (type)	Can combine with theme 1. REJECTED	Verbal				Messenger + emojis (with family), verbal (with a friend)	Verbal. Enjoys socialization.			Text immediate family	Verbal. Emails occasionally.	
Maintaining a diary	3. Awareness of daily moods? And their management. (Written record for tracking mood)	No	Agenda book. Appointments, important dates only.	Keeps a journal about things that happened, but does not maintain it regularly.	Started keeping a diary a long time ago, but didn’t continue.	No	No. “not for long.”	No	No. Did attempt to maintain one in the past, but “ quickly got tired of it.”	Kept a diary for 15 years while travelling. Did not self-report. Only wrote where she was on a given day and what she observed. No expressions in the diary.	Has done self-reporting for research studies but does not think it is accurate.	Never did self-reporting. Started journals but forgot to fill them.
Consciously aware of any behaviours attached to particular moods	Combine with 3. 3. Mood related behaviours.	Yes. Eating/Sleeping when bored.	No. “I'm too busy. I don't get bored. ”	Yes. Does not feel energetic or engaged, if proper sleep isn’t received. Also, mentioned overeating when nervous.	No particular behaviours associated to mood swings.			No. “I'm pretty inclined to stay the same all the time, yeah.” Cautious of an “over reaction” while replying to other people.			Tries to react to how other people are acting. No personal mood related behaviours.	No. Mentions about a brain condition that prevents him from keeping track of things.
If they experience mood fluctuations throughout the day	Combine with 3. 3. Awareness on mood fluctuations (if any), throughout the day.	No.	Only due to specific trigger events, and not naturally. Gets triggered by a fire alarm. Did mention not liking it when other people bring phone to the dining table.	Not too much.	Does have mood swings depending upon arthritic condition and pacemaker. But **not a lot of fluctuation.**	No. “I’m always about the same”.	No. “But my daily mood, I don't think it differs much. You get a new day, you don't bring all the other stuff with you, you can't have.”	No.	Not more than anybody else. Does feel low sometimes on a dim day, but it’s temporary.	No. “I consider myself a level-headed person” Had “surgical post operative depression” earlier once but got over it in 3 weeks with medication.	Not naturally. But could be triggered by news, or an observation, or conversation.	No.
Would find recording affective state/mood helpful	Irrelevant to the purpose of the study	No. “I don't know what purpose it would serve”	Depends if there is an incentive/reward associated with it.	Thinks it would be more valuable for younger people, as people of P3’s age would know how to change their mood by exercising, reading etc.	Does not think so.	No. “I don't think so because, I'm normally at the same level.”	Does not think so.	No. “most days I’m okay”	No. “I can manage well without a diary.”	No. “No, no, it just doesn't interest me. If you asked me to do that, I would not do it because I would find it **onerous** and **I don't think it would assist me**”	No. Would do it for research, but personally not.	Yes.

Active participation in any type of activity to cheer up or manage their mood. OR Consciously try to maintain a positive mood state by performing activities.	Mood management Combine with 3	No. Does not participate in the offered activities as they are not suited for her age.	Yes. Plays video games on PS 4. Resents TV. Socializes. Goes out on his scooter.	Tries to keep busy, so as to not think about things that might “take you down”.	Yes. Singing at the church choir, whistling, and social interactions (coffee time).	Talks every day with sister, and also with a friend.	Religious. Reads the bible. Has a positive outlook on life, and enjoys the environment of living, even after a major accident. Loves to discuss politics and religion, and to drink beer.		Yes. Group activities and interactions. “Yes, my time is well spent with management of my assets and staff, payroll, timesheets. I hire and I train staff here. ”	Adapts very well to change.		
How frequently should mood be recorded, given the assumption that they were to record it? ALSO FILLING: When should it be taken?	4. Requirements for tracking mood Frequency of recording mood, under assumption.	Depends on length of the process. Daily if the session is short (e.g., 2 mins)		Maybe 4-5 times a day. & Shouldn’t take too long. & Should be into the day and not at the beginning.	Comfortable with filling multiple times a day, but a single session should not last more than half an hour.		Would forget to fill out paper-based tests. Mentions “I might not be a good candidate for this”.		Daily would be sufficient.	Once a day, as, “Usually, I think over my day before I go to sleep, and that's the only time I think about it.”		Once a day.
Time it (one session of mood reporting) should take	4. Time								One minute. “I don’t want to waste more time than that.”	Not more than 10 minutes.	Less than a minute.	Fifteen minutes at most.
Would report multiple times a day?	4.	Maybe not. Once a day is okay.	Depends on how long it takes.	Depends on how long it takes. 3-4 times daily.	Yes					Once a day would be more than adequate.		
Preferred format for reporting mood, given the assumption that they were to record it?	4. Preferred format Also, under 4.	Digital i.e., on a smart device	Digital. Should be easily accessible. “I'll do it on the screen more easily”	Digital. Would prefer a list of choices.	Digital.	Digital.	Not digital. Does not possess smart devices (phone etc.)		Digital.	Paper-based format. (Even though the participant is familiar with technology use).	Would use Siri. Therefore, deducing it as digital.	Digital. Online journal.
Reminders or alarms	4. Under format Also, under 4.	Does not object	Should record mood change spontaneously as the change occurs. Fixed time mentioned in context of using phone at dinner table. Not for mood recording.	Would prefer spontaneous measurement over reminders.	Would prefer a reminder over spontaneous reporting.		Does not have a device for alarm. “But where’s that alarm going to be. I don't have a cell.”	No answer.	Would need a notification. “I would need a notification, absolutely”	No	Would prefer to record spontaneous changes and not on fixed timings (not reminder based).	Would prefer alarm or invoice.
Questionnaire easiest to understand	5. Favour/Preference/Approved	All were easy	POMS 2 SF A	Pick-A-Mood	POMS 2 SF A	VAMS-R		VAMS-R	All were easy	POMS 2 SF A	None were hard	POMS 2 SF A

									“There was nothing complex about that”			
Which questionnaire was liked the most	5. Favour/Prefer (combined)	POMS 2 SF A	POMS 2 SF A	“I can't say I liked anyone the most”			None		POMS 2 SF A		“Can't say I liked one more than the other because they all seem pretty similar”	
	5. Reason for preference	“I think it was more in depth.”	“A good variety of words and they express feelings and moods.”	“You could immediately see the expressions on their faces which convey their emotions.” Finds it straightforward. Does not dislike anything about it.	“It's almost like self-explanatory. The words seemed to flow together”	“It was easy to answer. You didn’t have to think too much.”	“I don't really have a preference.” SEE OTHER AT THE BOTTOM	“Easier to follow”	“The first one was more in detail. Also, because it was more challenging.”	“To me it's more analytical than the others.”	Would use the POMS 2 for self-reporting, when specifically asked this question i.e., if they were to self-report	“More to the point, More accurate”
Any measure hard to understand	5.		No. Some words were muddled. “There must be a synonym for that that will describe it more accurately”		No. Found them to be straightforward.	No	None “I'd be nit-picking if I did that.”	None	No but “Actually, they're very repetitious.” ## This was expected.	No	Pick-A-Mood	No
Least liked or disliked questionnaire	5. Disliked		None	VAMS-R Finds the vertical orientation of the subscales to be odd.			None	No	No “Like I said they are repetitious			Prefer not to use: VAMS-R
Reason for disliking	5.										“It just didn't appeal to me as a way of describing my mood. I thought the questions were better than the pictures.”	“Not accurate”
Other				The participant pointed out that there was no “TIRED” mood in Pick-A-Mood			For daily self report P6, would register on Pick-A-Mood because it is “quick”. (Specifically asked)					

Table 46: Analysis matrix