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Faculty of Engineering
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STRESS ASSESSMENT THROUGH GALVANIC SKIN RESPONSE USING SMART WATCHES

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Abstract

In recent years, many studies regarding the analysis of stress have attempted to replicate in the laboratory stress conditions that might occur in everyday life. Wearable devices were employed to collect and evaluate physiological signals in order to do this. Thus, the purpose of this study was to assess a stress condition by analyzing the skin conductance response signal through the use of the Empatica E4 wearable device. To understand the origin of the physiological signal analyzed, it was important to first understand the functions of the sweat glands and how sweating affects the electrodermal activity (EDA). EDA was divided into tonic component, slow and constant, and phasic component, more rapid and reactive, to then extract the characteristics and determine a stress situation. The latter can stress the body over time and have negative effects on health. The most common signs of stress are mood changes, damp or sweaty palms, difficulty sleeping and headaches. The body reacts to stress with a so-called "fight or flight" response, during which certain hormones, such as adrenaline and cortisol, are released. In accordance with the literature, the most commonly used way to detect stress is through the use of wearable devices such as smart watches as they are convenient and unobtrusive. Therefore, since this study is primarily aimed at detecting stress in the work environment, Empatica E4 was chosen for the above reasons. EDA reflects the activity of the sympathetic sudomotor nerve and is related to the electrical conductance of the skin, which varies with sweat production. EDA increases in response to a stress stimulus so that the skin conductance response (SCR) has a rapid increase that peaks in approximately 1 second, followed by a temporal decay with a half-life of approximately 3 seconds. The experiment was conducted on eight adult subjects for a duration of approximately 30 minutes for each participant. All wore the Empatica E4 bracelet on their nondominant hand for the duration of the test, making sure to hold it steady. The test consisted of a relaxation period followed by a moderate stress period, in which the subject had to think of a speech that was then to be presented in front of the examiner, and a more intense stress period consisting of an arithmetic test followed by a final relaxation phase. After the experiment the EDA signal was extracted which was then analyzed in Ledalab, a Matlab-based software, using Continuous Decomposition Analysis through which the tonic and phasic components of the signal were extracted. Subsequently, an algorithm was implemented in Matlab which allowed the signal to be divided into smaller windows of 60 seconds and the most important features such as the number of peaks, the average amplitude of the peaks, the standard deviation and the maximum value of the peaks were extracted. After conducting a statistical analysis on the number of peaks in each phase of the experiment, it was concluded that during the most intense stress phase there were more peaks with higher amplitude. In fact, in almost all subjects the number of peaks during the first half of the

experiment was zero while during the second half, that means from when the oral exposition of the speech followed by the arithmetic test began, the subjects showed an average of about 20 peaks per minute. We note, however, differences between more anxious subjects, who reached even 40 peaks per minute, and less anxious subjects, with an average of about 15 peaks per minute. This confirmed that through the use of smartwatches, specifically Empatica E4, it is possible to detect and assess a stress condition through the analysis of the electrodermal signal of the skin.

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Introduction

In recent years, many studies have been conducted regarding the analysis of stress in the workplace. In fact, many of these studies have tried to reproduce in the laboratory stress situations that may occur in everyday life. To do this, wearable devices have been used to then pick up physiological signals and analyze them.

Stress is identified as the reaction the brain has in response to sensory inputs from the eyes, nose or ears. When the body perceives a threat, which could be real or imaginary, the body's defensive mechanisms initiate a rapid automatic process called the "fight or flight" reaction. The brain immediately sends a danger signal to the hypothalamus, which is analogous to the brain's command center [1]. Typical physiological responses include changes in heart rate, skin temperature, pupil dilation, and electrodermal activity [2]. So, the physiological response of an individual to a stress event is called physiological stress.

The World Health Organization has dubbed stress "the health epidemic of the 21st century," with estimates that it costs American businesses up to $300 billion annually. Stress has a negative impact on both our mental and physical wellbeing. In a recent research conducted in the United States, more than half of those polled believed that stress has a detrimental impact on work productivity.

Stress levels in the United States grew by 10-30% across all demographic categories between 1983 and 2009. Numerous studies suggest that job stress is by far the most common source of stress among people, and that it has risen significantly over the decades. Increased job stress has been linked to an increased risk of heart attack, hypertension, obesity, addiction, anxiety, depression, and other diseases, as measured by the impression of having little control but numerous demands. Stress is a very individualized phenomenon that differs from person to person and types of tasks, based on individual vulnerability and resilience. The intensity of occupational stress is determined by the amount of the expectations imposed on the individual, as well as the individual's perception of control or decision-making authority in dealing with the stress. Of course, working stress isn't the only source of anxiety. The possible role of stress in the causation and/or exacerbation of disease in most organ systems of the body has been extensively researched. Stress is inextricably related to anxiety and plays a significant part in mental illnesses such as phobias, major depression, and bipolar disorder. As a result, lifestyle modifications that cause lifestyle stress have a significant impact on mental health [3].

Thus, it is important to recognize a stress condition as soon as possible in order to minimize damage and prevent stress from becoming chronic. So, there have been efforts in recent years to develop devices or non-invasive approaches to detect and prevent stress. The use of wrist sensors to detect stress has lately been extensively studied, and earlier studies have shown that stress may be detected relatively reliably. In most research, electrodermal activity, also known as galvanic skin response, is used as one of the biosensors in the recognition process.

In particular, the experiment conducted in this study aims to identify and detect moments or situations of stress through the analysis of the galvanic skin response using the wearable device Empatica E4 in laboratory environments.

1. Anatomy and Physiology

1.1. Anatomy of the skin

The skin is the largest organ in the body, accounting for around 15% of adult body weight. It serves a variety of critical tasks, including defense against external physical, chemical, and biological threats, as well as prevention of excessive water loss and thermoregulation.

The epidermis, dermis, and subcutaneous tissue are the three layers that make-up the skin (figure 1). The epidermis, or outermost layer, is made up of keratinocytes, which generate keratin, a long, threadlike protein that serves as a protective layer. The dermis, or middle layer, is primarily made up of collagen, a fibrillar structural protein. The dermis sits on top of the panniculus, a layer of subcutaneous tissue that contains little lobes of fat cells known as lipocytes.

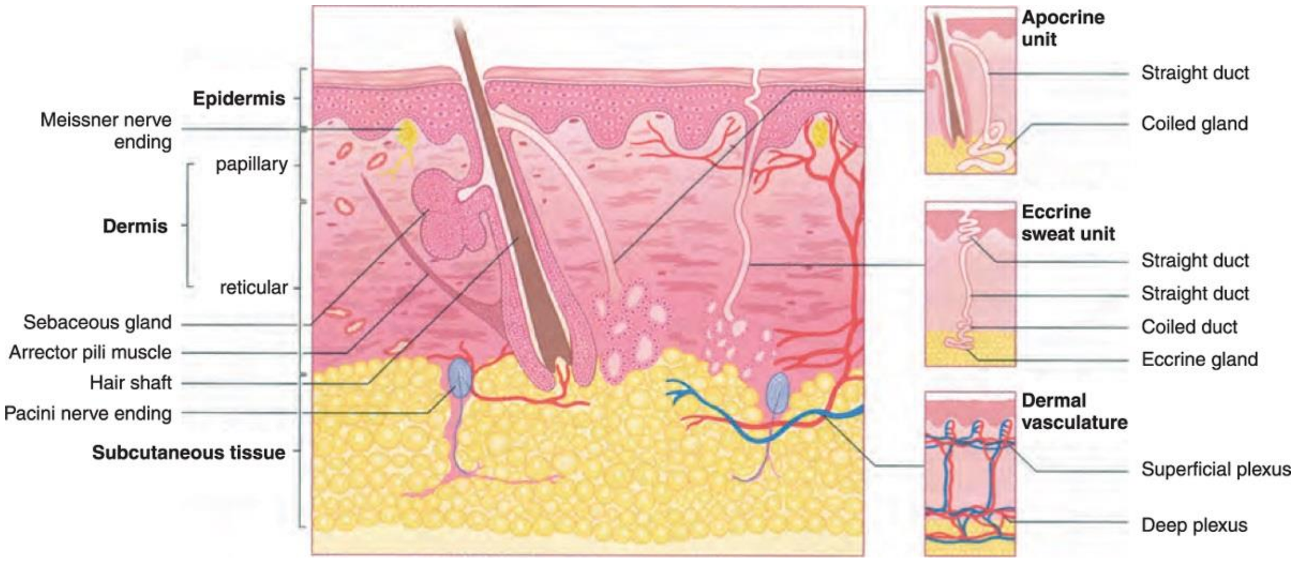


Fig. 1 Cross section of skin and panniculus [4].

Epidermis is a stratified squamous epithelial layer made up mostly of two cell types: keratinocytes and dendritic cells. Intercellular bridges and a substantial volume of colorable cytoplasm distinguish keratinocytes from "clear" dendritic cells.

The basal cell layer, squamous cell layer, granular cell layer, and cornified or horny cell layer are the four layers that constitute the epidermis. The basal layer is the epidermis' principal source of mitotically active cells that give rise to the outer epidermal layers' cells. Columnar-shaped keratinocytes connect to the basal membrane area with their long axis perpendicular to the dermis in the basal layer. Desmosomal connections connect these basal cells to one other and to the more superficial squamous cells, forming a continuous layer. Basal cells are also distinguished by their oval or elongated dark-stained nucleus and the presence of melanin pigment transferred from adjacent melanocytes.

The squamous cell layer, also known as the stratum spinosum, is a 5-10 cell thick epidermis layer that covers the surface of the basal cell layer. The squamous layer is made up of a range of cells with different shapes, structures, and subcellular features depending on their location. Suprabasal spiny cells, for example, are polyhedral in shape and have a rounded nucleus, but cells in the top spiny layers are bigger, flatten as they approach the skin surface, and contain lamellar granules. Desmosomes abound in the intercellular gaps between spiny cells, promoting mechanical connection between epidermal cells and providing resistance to physical pressures.

The granular layer, also known as the stratum granulosum, is the epidermis's most superficial layer containing living cells. It is made up of flattened cells with numerous keratohyalin granules in its cytoplasm. These cells are responsible for the further synthesis and modification of proteins involved in keratinization. The thickness of the granular layer changes in proportion to the thickness of the overlaying corneal cell layer. For example, the granular layer under areas with thin cornified layer may be only 1-3 cell layers thick, whereas the granular layer under the palms of the hands and soles of the feet may be 10 times this thickness.

Corneocytes (corneal cells) in the cornified layer give mechanical protection to the underlying epidermis as well as a barrier against water loss and foreign substance penetration. A continuous extracellular lipid matrix surrounds the protein-rich, lipid-poor corneocytes. The nuclei of large, flat, polyhedral corneal cells have been destroyed during the terminal differentiation, and they are technically dead. To encourage desquamation moving outward, the physical and biochemical features of cells in the cornified layer vary depending on the location. Because of the high quantity of free amino acids in the cytoplasm of cells in the middle layer, they have a considerably better ability to bind water than cells in the deeper layers. Deep cells are also denser and have a wider range of intercellular connections than cells in the more superficial layers.

The epidermis must maintain a relatively constant number of cells and control connections and junctions between epidermal cells as a tissue that is constantly regenerating. As cells reposition themselves during their development, adhesions between keratinocytes, interactions between keratinocytes and immigrant cells, adhesion between the basal lamina and the underlying dermis, and the process of terminal differentiation to generate corneocytes must all be regulated. The underlying dermis regulates epidermal morphogenesis and differentiation in part, and it also plays a vital role in preserving postnatal structure and function. In the development of epidermal appendages, the epidermal-dermal interface is also important.

A porous zone of the basement membrane forms the contact between the epidermis and dermis, allowing cell and fluid exchange while also holding the two layers together. Dermal-epidermal junction structures are mostly composed of basal keratinocytes; dermal fibroblasts are also involved, but in a lesser amount.

The basal lamina is a layer composed mostly of type IV collagen, as well as anchoring fibrils and dermal microfibrils, that is produced by the epidermis' basal cells. This includes the lamina lucida, an electron-lucent zone, as well as the lamina densa. Rivet-like hemidesmosomes bind the plasma membranes of basal cells to the basal lamina, distributing tensile or shear pressures across the epithelium. The dermo-epidermal junction delivers developmental signals, defines cell polarity and growth direction, directs cytoskeleton organization in basal cells, and acts as a semipermeable barrier between layers [4].

1.2. Physiology of the Skin

The epidermis is a continuously renewing layer that gives rise to derived structures like the pilosebaceous apparatus, nails, and sweat glands. Eccrine glands, apocrine glands, and apoeccrine glands are the three basic types of sweat glands as shown in figure 2.

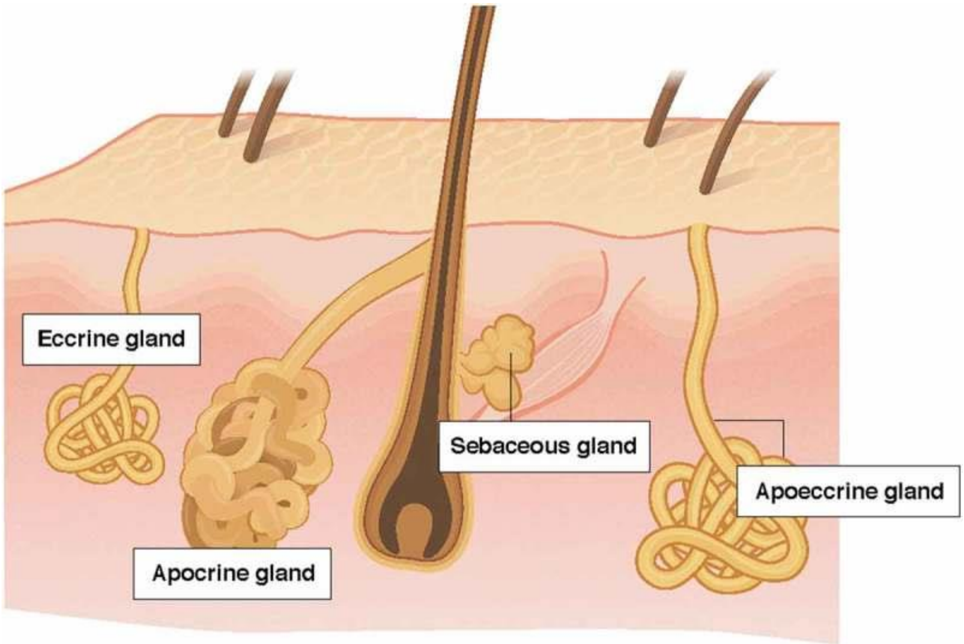


Fig. 2 Sweat glands [5].

Heat control is aided by *eccrine sweat glands*, which are most abundant on the soles of the feet and least abundant on the back. The eccrine sweat glands are the most abundant and produce the biggest amount of perspiration. When a stimulus, such as an object, a person, or an event, is recognized as personally significant and causes an emotional reaction, the brain sends a signal to the eccrine sweat glands to activate them via the sympathetic branch of the autonomic nervous system, resulting in sweat secretion and an increase in skin conductance. Eccrine sweat glands are made up of epithelial cells that develop downward from the epidermal ridge. The spiral intraepidermal duct, the straight dermal section, and the spiral secretory duct are three composite elements of the eccrine sweat unit that are generated during development from this tubular, or ductal, structure. The spiral duct is made up of dermal duct cells that have migrated upward and opens on the skin's surface. Within the duct, the cells undergo cornification, and the corneocytes that are formed eventually become part of the cornified layer. The superficial spiral duct is connected to the gland's internal secretory component by the straight dermal segment. The eccrine unit's secretory spiral is made up of glycogen-rich clear secretory cells, black mucoid cells, and contractile myoepithelial cells that are found deep in the dermis or inside the superficial panniculus. Intercellular canaliculi are formed when two clear cells join on the basement membrane or myoepithelial cells. The canaliculi open into the gland's lumen immediately. In reaction to a heat stimulus, large glycogen-rich inner epithelial cells start sweating. Darker mucoid cells in the secretory spiral and dermal duct actively reabsorb sodium from sweat in the duct, resulting in a very hypotonic solution released to the skin surface through the intraepidermal spiral duct.

While eccrine glands are responsible for heat control, *apocrine glands* are responsible for odor production. Human apocrine sweat glands are mostly found in the armpit and perineum, and unlike eccrine and apoeccrine sweat glands, they do not open directly onto the skin surface. Instead, the intraepithelial duct enters the infundibulum above the sebaceous duct and opens into pilosebaceous follicles. Apocrine glands' basal secretory coil, which is generally found entirely in subcutaneous fat, differs from eccrine glands' in that it is totally made up of secretory cells, with no ductal cells. Furthermore, whereas apocrine glands are present from birth, their secretory function does not begin until puberty.

The *apoeccrine sweat gland*, on the other hand, grows from eccrine-like precursors throughout puberty and opens directly into the skin. The apoeccrine sweat gland is present in the armpits of adults and was discovered during the isolation of human axillary sweat from patients with axillary hyperhidrosis, a disorder defined by abnormally elevated sweating rates. Its relative frequency varies from person to person and, with a secretion rate up to 10 times that of the eccrine gland, is assumed to contribute to axillary hyperhidrosis [4] [5].

1.3. Electrodermal Activity

Electrodermal activity (EDA), also known as galvanic skin response (GSR), is a measure of electrical activity on the surface of the skin and is influenced by the amount of sweat produced by an individual.

The reticular formation, hypothalamus, amygdala, premotor cortex, and prefrontal cortex have all been related to increased electrodermal activity.

Electrodermal activity has multiple functions, including physical movement and thermoregulation, as well as psychological states such as emotion and attention [6]. One or two approaches are commonly used to test the electrical characteristics of the skin. Electrodes that penetrate the skin and allow voltage to be measured through the skin are used in the endosomatic method. To assess the resistance, conductance, impedance, or admittance of the skin, exosomatic techniques use a pair of Ag-AgCl skin electrodes that provide direct or alternating current. Direct current is commonly used to measure SC.

The EDA SC time course consists of the SC level (SCL) and the SC response (SCR). The skin conductance level is the tonic component that changes slowly over minutes (within 10 seconds up to 1 minute). It is derived from sweat that diffuses into the skin and is produced by the secretory part of the gland. The skin conductance response, on the other hand, is the phasic component caused by the rapid release of sweat through the opening of the ducts, which is triggered by the sympathetic sudomotor nerve (SMNA) consisting of a single, short nerve burst. SCR rises above the tonic level with rapid fluctuations, so it is easy to find peaks and bursts that could provide valuable information for identifying emotional stimulus events. Generally, the duration of the stimulus event is about 1-5 s after the onset of the emotional stimulus. In the figure 3, the features that characterize the SCR are highlighted.

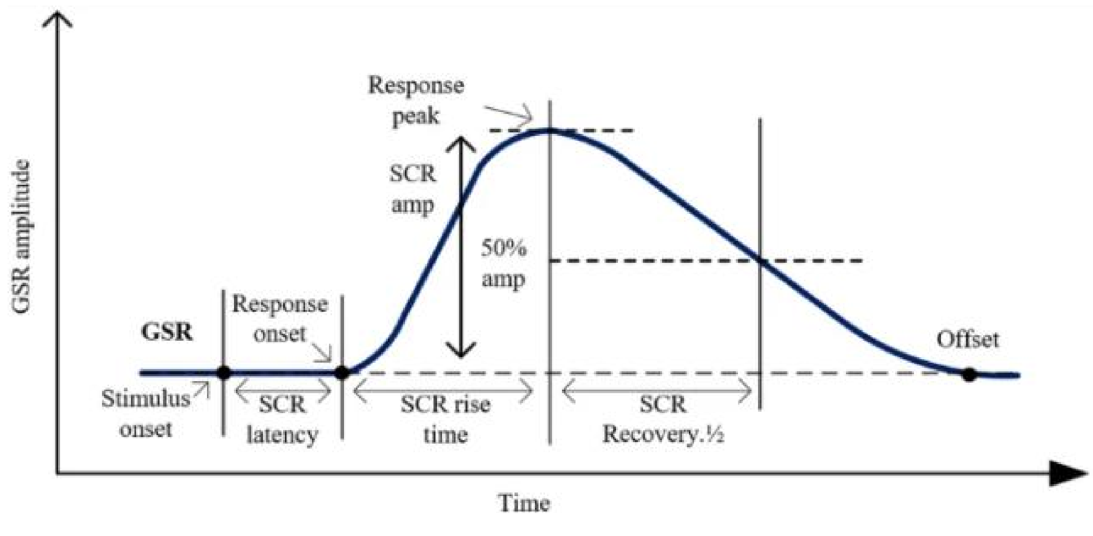


Fig. 3 EDA signal and relevant parameters [7].

Skin conductance responses are extensively studied in psychological and neuroscientific research and have been used as a general reporter of psychophysiological stress [8]. EDA can be utilized as an objective measure of emotional states due to the connection of cognitive processes, arousal, emotion, and attention.

EDA can also be utilized to investigate unconscious emotional reactions that occur without conscious knowledge or are unrelated to cognition (e.g., threat, anticipation, salience, novelty).

EDA has recently been discovered to be a helpful indicator of attentional processing, with salient stimuli and resource-intensive tasks evoking higher EDA responses. EDA surveys have also been used to illuminate broader areas of inquiry such as: psychopathology, personality disorders, conditioning, and neuropsychology [6].

2. Stress detection

2.1 Stress and Causes

In recent decades, the concepts of stress have evolved and expanded significantly. The stress system, according to many scientists, consists of numerous components, including the stressful stimuli, the stressor, and the stress response. Because the stress response on the body is so comparable to other signal transduction processes, stimuli, receptors, and cascades should all be included. As a result, the stress system should be composed of five basic components: a stressful stimulus, a stressor, a stress, a stress response, and a stress effect (Figure 4). The stressful stimulus is the starting point, the effect is the end point, and the stressor, stress, and stress response are all cascades. Notably, the stress system's basic structure lacks a "sensor", making it impossible to establish which stressors can and cannot induce stress. Fortunately, in the 1920s, Cannon coined the term "homeostasis," which refers to a system's tendency to maintain the stability of its internal environment and discovered a wide range of threats to homeostasis that elicited a sympatosurrenal response he called the "fight or flight" response, which is now recognized as a typical stress response. As a result, homeostasis could be a candidate for the stress system's "sensor". Stress, according to Cannon, is a danger to homeostasis. The biological repercussions of stress include restoring homeostasis, which promotes health (positive effects), or causing harm to the body or even disease (negative effects).

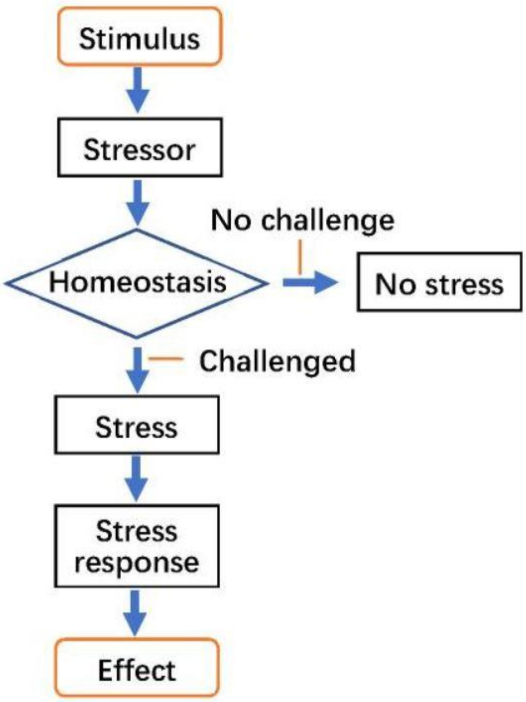


Fig. 4 Structure of the stress system [8].

The concept was later expanded to the field of psychology, and evidence accumulated indicating autonomic nervous system activation was more sensitive to emotional than physiological activities. Emotional stress, cognitive stress, perceptual stress, and psychosocial stress were the four primary categories of psychological stress, and each category was occasionally further subdivided depending on specific psychological factors or stimuli, such as social defeat stress, post-traumatic stress, and pandemic stress [9].

Stress can be short-term or long-term. Both can cause a wide range of symptoms, but chronic stress puts a strain on the body over time and can have long-term health consequences. Some common signs of stress include mood changes, wet or sweaty palms, difficulty sleeping, headaches, and other symptoms. Stress isn't always easily noticeable; while it can come from an obvious source, little daily worries from job, school, family, and friends can also place a burden on the mind and body. Certain hormones, such as adrenaline and cortisol, are released during the body's response to a threat, the so-called fight or flight response, as previously mentioned. This increases heart rate, slows digestion, redirects blood flow to main muscle areas, and alters several other autonomic nerve activities, providing a burst of energy and energy to the body. The relaxation reaction is aimed to return the systems to normal operation once the perceived threat has passed. However, in cases of chronic stress, the relaxation response isn't activated frequently enough, and being in a near-constant state of fight or flight might damage the body.

Stress has an emotional impact as well. While a small amount of stress can cause moderate anxiety or frustration, long-term stress can cause burnout, anxiety disorders, and depression.

There is no single, particular treatment for stress because it is not a distinct medical diagnosis. Change the circumstances, improve stress management skills, adopt relaxation techniques, and treat symptoms or disorders that may have been created by chronic stress are all part of stress treatment [10].

2.2 Stress Monitoring

Stress is an issue that is currently attracting a lot of attention, not only in research but also in everyday life. Researchers in a variety of professions are working to develop new methods for assessing, monitoring, and reducing stress that will not only address public interest but also help to better understand the phenomenon [11].

Stress is experienced in a wide range of situations, including family pressures, personal finances, academics, and other situations. Any stimulus that causes a stress response is a stressor, which is defined as any environmental change that causes a shift toward a lower state of usefulness. In other words, a stressor is anything that causes a homeostatic imbalance and elicits a biological or behavioral response to correct this imbalance, as also said before.

Some studies have brought evidence to support heart rate variability (HRV) being used as an objective assessment of stress and mental health. However, because HRV is associated with various stressors, duration of stress, individual ability to cope with stress, and lifestyle habits, these studies are difficult to interpret [12]. On the other hand, researchers have found that also electroencephalography signals (EEG) intrinsically associated with perceivable features that change in different situations will change. Therefore, by extracting these features and analyzing them, a fair perception of the nervous system could be obtained defining a situation of stress [13].

Anyway, according to a review of the literature, EDA signal is the most relevant physiological marker for detecting stress. EDA signals are typically collected using two measurement sensors on the skin of the fingers or feet, whereas, for example, ECG signals require an additional chest sensor. Wearing fewer sensors may cause less discomfort and difficulty in the real world. In addition, given the economic scales and the necessity to leverage existing products such as smart watches, EDA sensors can be easily combined with a smart watch in the long term.

In fact, since it is really important to immediately identify a stress condition in order to decrease the damage and prevent stress from becoming chronic, in recent years there have been efforts to develop devices or non-invasive methods to detect a stress condition and make sure to prevent it.

Wearable devices have been the ones that have gained the most importance due to their reliability and non-invasive monitoring of the parameters of interest [14]. Among them, the most widely used has been Empatica E4 although some studies have been done using devices such as the Polar H7 [15], J!NS MEME electrooculography goggles [14] and other types of devices or comparing Empatica E4 with devices such as the Samsung Gear smartwatch [16] and the MindWare Mobile [17]. These wearable technologies are very useful to monitor a person's physiological signals continuously and automatically through multiple sensors.

Many studies have been carried out in the laboratory by reproducing situations of stress and calm and then monitoring the various physiological signals of the patients considered. The most frequently used signals, as mentioned before, were electrodermal activity, cardiovascular activity and brain activity.

In the study [18], the keyboard and mouse activity of 93 office workers was analyzed for approximately two weeks of work. The relationship between self-reported effort, reward, overload, and perceived stress and the duration of computer use recorded by the software, the number of short and long breaks at the computer, and the rate of use of the input device was analyzed. Breaks were found to be 20% less for the most stressed and lowest reward workers. These outcomes support the hypothesis that employee computer use patterns vary among individuals with different levels of workplace stressors.

In [19], a wearable sensor system called AutoSense was able to detect cardiovascular, respiratory, and thermoregulatory measurements, via an armband with four wireless sensors and a chest strap with six wireless sensors. AutoSense was complemented by a software framework on a smartphone that processes sensor measurements received from AutoSense to infer stress factors. The use of AutoSense on over 20 subjects resulted in the first stress model with 90% accuracy.

In the work reported by [20], twenty participants underwent two mental tasks using SHIMMER sensors capable of detecting ECG signal via an elastic chest belt and three electrodes, GSR signal via a wrist strap, and accelerometer data via a sensor placed on the waist belt. The activity information derived from the accelerometer allowed to achieve an accuracy between 80% and 90% in mental stress classification.

In [21], a study was conducted for stress detection using Nexus 5 smartphone sensors. The application used for stress assessment was based on the Funf framework and collected behavioral and context data that was then uploaded to a server in SQLite format. The results showed an average accuracy of 73% in a high and low stress classification using only behavioral and contextual data received from the cell phone.

Similarly, in [22], sensors from the smartphone's built-in accelerometer (Samsung Galaxy SIII Mini) were used to detect behavior related to stress levels in 30 subjects. The study lasted 8 weeks and was conducted in real work environments, with no constraints on smartphone use. Subjects reported their stress levels three times during their work hours. With the use of statistical models to classify reported stress levels, an accuracy of approximately 71% was achieved for user-specific models. By the way, the current state-of-the-art studies for automatic stress detection propose a methodology using smart watches. In particular, many studies have used the wearable device Empatica E4 that can detect physiological signals in real time.

In the study [23] they compared Empatica E4 with a reference device by subjecting subjects to an experiment that consisted of two types of tasks: sing a song stress task and noise task. In order to see if Empatica E4 was a good enough device, the signal level, the parameter level and the event level were compared with the reference device and they came to the conclusion that Empatica E4 is a good device if used for long periods of time so as not to have consistent data loss. Similarly, in [8] they compared Empatica E4 with different models of Samsung Gear smart watches by subjecting 21 participants to three types of sessions (e.g. giving a speech in public). The collected data were used with famous algorithms in the literature such as, for example, Random Forest or Multiplayer Perception deriving an accuracy degree of 90.40% for the E4 device and 84.67% for the Samsung devices.

The work described in [24] compared the E4 device with wearable sensors to a device with stationary sensors. In his study, seven participants performed two tests: one that simulated a job interview and one that consisted of reading a text aloud for 5 minutes in order to recreate a situation similar to the interview but without stressful elements. The two signals obtained from E4 and the laboratory instrument have been compared showing that E4 is a valid device that allows good performance for stress detection.

Instead, in [17] they compared E4 with MindWare mobile for the detection of inter-beat interval (IBI), HRV and EDA signals. These three signals were acquired from 30 students during a resting situation, at the beginning and end of the experiment, and during a dyadic conversation using E4 and MindWare mobile simultaneously. It came out that E4 was less accurate for measuring HRV and EDA due to having some missing data probably due to movement or its poor placement.

A study conducted by other researchers [25], attempted to create an algorithm that could be a gold standard of physiological responses to stressors. E4 was associated with the EDiary app which, with a geolocation system, recorded the location of one's location at the time a stressful situation was recorded. The algorithm consisted of scoring the various GSR and skin temperature (ST) values after a hypothetical stimulus. Studies conducted in real life have taken this algorithm as a reference, recording an accuracy of 84%. Often a high level of accuracy is given by the combination of several signals recorded at the same time and sometimes even leaving out the EDA signal.

In fact, in the study [26], signals of 15 subjects from an existing database were considered, divided into time windows and then features were extracted. The latter were then classified using three types of classifiers: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and Random Forest (RF). The highest accuracy was achieved with the LDA classifier using the combination of ST, blood volume pulse (BVP) and heart rate (HR) without considering the EDA signal at all due to its poor accuracy.

In the study [27], where the aim was to understand which signal gave higher accuracy, using the ST signal with the RF algorithm was found to be 92% accurate with context and 76% accurate without context.

The work detailed in [28] collected data from sixteen participants recruited to create low-cost wearable devices by subjecting them to stress sessions interspersed with relaxation sessions such as doing yoga. MultiLayer, Random Forest, Linear Discriminant Analysis, Principal Component Analysis and K-Nearest Neighbors algorithms were used to recognize various levels of stress. The accuracy obtained considering the combination of the three signals HRV, EDA and accelerometer (ACC) was 85.36% using the LDA algorithm also considering the relaxation phases, as opposed to the accuracy obtained without considering the relaxation which was 98% using the MLP and RF algorithms.

The work of [29] sought to develop a method for stress detection that can accurately, continuously, and discretely monitor psychological stress in real life. They subjected 21 people to a test consisting of solving equations in their heads within a certain time limit and then applied the laboratory stress detector to real-life data. When context was not stated, the accuracy of the stress detector was 7% while when context was stated, the accuracy increased to 95%. The information on the context was very important because it allowed to distinguish between psychological stress and physiological stress due for example to eating or exercise.

Two similar studies, [30] and [31], used a different approach from those seen previously. The first study, [30], consisted of determining a calm or stressful condition by showing the participant images or videos taken from the IAPS library. The data were acquired with E4 and were then processed with EmoSys software, which was able to separate each acquired signal. The signals were filtered, and 23 features were extracted and classified using support vector machine (SVM). Building on this initial study, in the second study, [31], 147 participants were subjected to an experiment that consisted of showing scenes from movies that instilled fear or joy while physiological signals were recorded by the E4 device. The purpose of this study was to compare the SVM classifier with the deep-SVM (D-SVM) classifier to determine what the minimum range was for recognizing a stressful situation. The D-SVM is given by sort of overlapping SVM sublayers in order to get the best features. It was found that using only SVM it has an accuracy between 75% and 90% as opposed to D-SVM which has an accuracy of 92% and is able to recognize a stress condition in less time (after only 3 seconds).

In the study [32], twelve subjects were subjected to a laboratory experiment that consisted of interacting with a laptop where the Stroop Task was installed while the subjects wore the E4 smartwatch and headphones to interact with the environmental trigger (fire alarm). Since a stress detector was implemented, which consisted of EDA signal acquisition, filtering, discretization with SAX (it consists in reducing a time series to real values of length n in a string of symbols long w) and distinction between stress and calm, the stress perceived by the subjects was compared with the stress detected by the detector detecting an accuracy of 79.17% and an accuracy of 60%.

On the other hand, the article [14] presented a study with the aim of monitoring stress with the E4 smartwatch and the J!NS MEME glasses. Five participants were subjected to an experiment that consisted in simulating manufacturing activities such as assembly and manual manipulation by wearing the two devices and creating models using LEGO bricks. Also, in this study feature classification was done by SVM using Gaussian Radial Basis Function showing an accuracy of 92.7%.

So, based on the conducted studies, the state of the art and future studies to improve the analysis of stress it emerged that one of the most used devices for stress assessment is Empatica E4. As also said before, the choice to use this device was made because it is the least obtrusive and therefore the most suitable for a better stress analysis.

2.3 Relationship between stress and worker behaviour

One of the most interesting viewpoints on stress is occupational stress. Occupational stress affects individuals on a personal level, but it also has an impact on organizations, particularly in terms of its economic impact. Increased medical insurance costs, increased demand on medical facilities and professionals, lower productivity, human error, absenteeism, and other factors, for example, all contribute to economic losses. This necessitates the creation and implementation of stress management measures that can both save costs and improve workplace well-being and quality [33].

In order to find a solution to what stressful workers mean in economic terms, it would first be necessary to consider the effects that stress has on their physical and mental health. The most common symptoms of a stressed worker are irritability, anxiety, depression, headaches, insomnia and difficulty concentrating. So, before focusing on improving stress for financial feedback, it is good to consider these issues.

Although it may be impossible to completely de-stress the workplace, companies should have indicators in place to determine the size of the company's stress problem. Monitoring absenteeism is one strategy for tracking employee stress, but other options include keeping a close eye on retention issues, the annual employee satisfaction survey, the amount of employee grievances, and unusual productivity decreases. Anyone might simply observe and search for individualized symptoms of stress, such as facial expressions, inappropriate language, and tightness [34].

Technological advancements, competitive lifestyles, and a variety of other societal variables are all elements that contribute to work stress. Workplace stress is a double-edged sword that may be both productive and counterproductive. It can be advantageous if it encourages or motivates employees to work harder and better, allows them to explore new possibilities, and increases work productivity. It can be counterproductive when external factors increase job pressure but do not produce effective result.

Job stress is a part of everyone's daily lives, and it has an impact on their work performance. Overwork, workload, low salaries, lack of incentives, motivation to work, technological changes, low morale, and lack of recognition can all contribute to job stress. Therefore, it's necessary to figure out how demographics affect employee workload, job security, and shift work, as well as to examine the relationship between factors that contribute to job stress and job performance.

The results of a study conducted at the Aavin company in South Africa led to some recommendations for reducing worker stress. First, the workload of employees can be minimized, and management can make efforts to efficiently delegate work. Alternate shifts can be assigned to employees, allowing them to maintain a healthy work-life balance. A job stress audit can be conducted on a regular basis to determine the source of job stress and how to alleviate it. Seminars and workshops on holistic work-life balance might be organized by the company [35].

2.4 Clinical tests

Protocols that allow researchers to investigate the biological pathways of the stress response in health and disease are crucial to the advancement of stress and anxiety research. Although there are several procedures for inducing the stress response in the lab, many of them neglect to provide a naturalistic context or include features of social and psychological stress.

The Trier Social Stress Test (TSST) appears to be the most useful and acceptable standardized procedure for stress hormone reactivity investigations, according to the meta-analysis of psychological stress protocols. The TSST has been adapted to accommodate the demands of many research groups, but it typically consists of a waiting period upon arrival, anticipated speech preparation, vocal performance, and verbal arithmetic performance phases, followed by one or more recovery periods as shown in figure 5. The TSST has identified social appraisal and unpredictability as significant elements of stress induction. The Trier Social Stress Test, which involves a public speaking test followed by an arithmetic calculation, is a common method for quantifying acute stress. After the subjects have completed these tasks, their saliva, blood, psychophysiological, and cognitive measures are analyzed to determine their stress levels. As a result, the TSST is a good substitute for physical stressors since it simulates the more naturalistic psychological stress of performing in front of an audience [36].

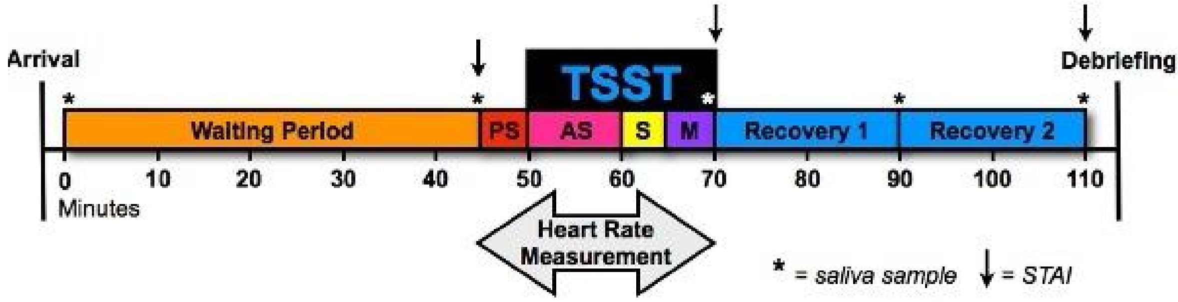


Fig. 5 Experimental protocol [36].

In this figure the phases of the Trier Social Stress Test (TSST) are represented; 5-minute Pre-Stress period (PS); 10-minute Anticipatory Stress period (speech preparation) (AS); 5-minute Speech period (S); 5-minute Math period (M).

The Perceived Stress Scale (PSS), on the other hand, is a measure used by medical experts to assess an individual's overall stress levels prior to any physical or psychological intervention. PSS is a short survey that asks a person a series of questions about their last month of life on a scale of 0 (never) to 4 (very often). "How many times have you been upset because something unexpected happened?" and "How many times did you feel like things were going your way?" are two examples of the types of questions that are asked. These questions are designed to determine the amount to which a person's life has been "unpredictable, unmanageable, and overcrowded" in the previous month, and hence their stress level.

The Kessler Psychological Distress Scale (K10) employs a series of ten questions to assess the level of mental distress a person is feeling, comparable to the PSS. These questions, such as "Have you felt nervous?" and "Have you felt depressed?" are answered on a scale of 1 (never) to 5 (always) based on the previous month. These questions were designed to assess people's mental health by addressing depressive, anxious, and other psychologically distressing symptoms. K10 has been proved to be accurate and dependable in determining cases and non-cases in the DSM-V (Diagnostic and Statistical Manual of Mental Disorders) [36].

2.5 Stress monitoring with wearable sensor technology

The stress response allows the body to overcome obstacles and prepare for threats, but sustained levels of stress can damage health. Stress has long been measured through physical tests and questionnaires that rely primarily on user input, which can be subjective and inaccurate.

Recently, analytical detections of biomarkers related to the stress response have been established to quantify the amount of stress the body is experiencing biologically. As part of wearable and flexible devices, new stress sensing devices focus on detecting cortisol in sweat. These devices promise continuous, real-time stress data collection that can be used in clinical diagnoses or for personal stress monitoring and management.

The general public is likely more sensitive to their health and history than ever before, thanks to smartwatches, fitness trackers, and the general desire for smart, home-based health services. Many real-time stress monitoring devices rely on photoplethysmographic data, and other researchers have combined photoplethysmographic data with other physiological signals such heart rate variability or ECG data.

On smartphones, there are several stress management apps that give coping skills like breathing, mindfulness, and mediation to help overcome a stressful lifestyle. Apps that are evidence-based can be used to supplement medical care, but they cannot assess stress levels. Researchers are developing technologies that can offer useful, concrete data through the detection of certain stress biomarkers for stress monitoring in order to better evaluate stress [37].

3. Electrodermal Activity and Stress

3.1 Electrodermal Activity behaviour under stress conditions

The tonic and phasic changes in electrodermal activity are regulated by sympathetic innervation of the sweat glands. Sudomotor nerves are sympathetic nervous system postganglionic nerve fibers that only innervate the eccrine sweat glands and the dermal duct. They regulate sweat synthesis, duct opening, and sweat secretion in this way. Sweat in the gland, sweat dispersion to the skin, and sweat secretion through the duct opening all influence the electrical characteristics of the skin. As a result, EDA reflects the SMNA activity delivered to the sweat gland.

EDA is linked to central mechanisms that control gross movements, thermoregulatory sweating, affective processes, orientation, and attention and control, among other things. EDA is a measurement of electrical conductance changes in the skin that has a significant link to sweat production. Because the eccrine sweat glands are not innervated by the parasympathetic nervous system, EDA only reflects activity in the sympathetic branch of the autonomic nervous system (ANS) [38].

Skin electrodermal activity was one of the earliest methods of assessing the electrical resistance of the skin employed in psychological study. EDA increases in response to a stressor, but basal resistance decreases, according to experimental evidence. It is sensitive to both immediate and long-term emotional arousal, as well as changes in mood or stress stimuli. Because sympathetic nerve activity regulates sweat gland activity, this measurement is a good technique to track autonomic nervous system activity. The number of sweat glands varies across the human body but is largest in the hands and feet (200-600 sweat glands per cm^2), where the EDA signal is normally collected. The skin conductance response is an objective, transient indication of the autonomic nervous system in response to a stimulus. Both positive (happy or joyful) and negative (threatening or sad) stimuli have been found to elicit an increase in arousal - and hence in skin conductance. As a result, the EDA signal represents the intensity of the emotion rather than the type of emotion. While sweat secretion is vital for thermoregulation and sensory discrimination, emotional excitement also causes changes in skin conductance: the higher the arousal, the higher the skin conductance [39].

As mentioned in the previous chapter, two types of procedures are commonly used to measure the electrical characteristics of the skin. Exosomatic techniques, which generally use a pair of Ag-AgCl skin electrodes that deliver direct or alternating current to determine the resistance, conductance, impedance, or admittance of the skin, and endosomatic techniques, which use skin-penetrating electrodes that allow voltage measurements through the skin. Skin conductance is often measured using direct current (SC).

EDA SC times are composed of SC level (SCL) and conductance responses (SCR). The tonic component is the skin conductance level, which fluctuates slowly over a few minutes. The amount of skin conductance is determined by the diffusion of sweat produced by the gland's secretory part onto the skin. The phasic component of the skin conductance response is induced by the quick release of sweat through the ductus opening, which is initiated by a single, short nerve burst activated by SMNA. SCR has a fast ascent that peaks in about one second, followed by a decaying time course with a half-life of about 3 seconds. The effect of phasic SMNA is thus reported by skin conductance responses. Skin conductance responses have been used as a general reporter of psychophysiological stress in psychology and neuroscientific studies. Skin conductance levels have frequently been used as measures of sympathetic SMNA aggregate levels, however unlike SCRs, they cannot provide informations about event-related phasic SMNA.

Peak amplitude, which is simply defined as the difference between the SCR's peak and valley, is measured as part of the skin conductance response analysis. However, because SCRs frequently overlap, earlier and later SCRs might cause difficulties in recognizing the true depression, resulting in errors in the observed peak amplitude. According to certain studies, a transient burst of SMNA causes temporary duct opening and sweat release, all of which happen far faster than the SCR's time course. Researchers considered these findings in the context of linear systems theory, which led them to do a "deconvolution analysis" on the SC time series. Individual SCRs are extracted using this method, allowing for accurate peak amplitude measurements [40].

4. Materials and methods

4.1 Participants

In total, eight participants who were all workers (between 26 and 42 years old) took part in the experiment for a period of approximately 30 minutes on 5 different days. The test to which they were subjected was the TSST readapted for time and space requirements. Two rooms were provided to conduct the test, one for the participant and one for the examiner. During the speech preparation and relaxation periods the participant was always alone in a room while during the vocal performance and mathematical test the examiner was with the participant. Throughout the experiment each subject was seated with the non-dominant hand (in this case always the left hand) immobile resting on a desk.

4.2 Materials

The biosensor used in the present study was the E4 wristband from Empatica as shown in figure 6. The E4 is a wearable device designed to collect continuous, real-time data in everyday life. The device can measure a variety of psychophysiological responses in the body. The E4 has four sensors in total: a PPG sensor, an EDA sensor, a 3-axis accelerometer, and a temperature sensor. The current study focused on SCR, which was assessed using an EDA sensor. An internal real-time clock and a function to set event markers are also included in the sensor. Furthermore, the E4 has a data storage capacity of over 60 hours and can run for over 36 hours.

Fig. 6 Empatica E4 with the position of its sensors [41].

During the experiment, E4 was worn tight enough that the EDA electrodes did not change position on the skin, but not so tight that blood flow was restricted, or discomfort was experienced. Before using Empatica's services, such as the E4 connect online application, E4 manager, and E4 realtime app, it's necessary to create an E4 connect account. On a secure cloud platform, E4 connect allows users to view, organize, evaluate, and download recorded data (from both recording and streaming modes) as shown in figure 7. As a result, E4 connect is a secure cloud-based repository where users may access, and control data uploaded by their E4 wristband. It offers list and calendar views for navigating a session, a dashboard for viewing data, and download links to access the raw data with third-party applications.

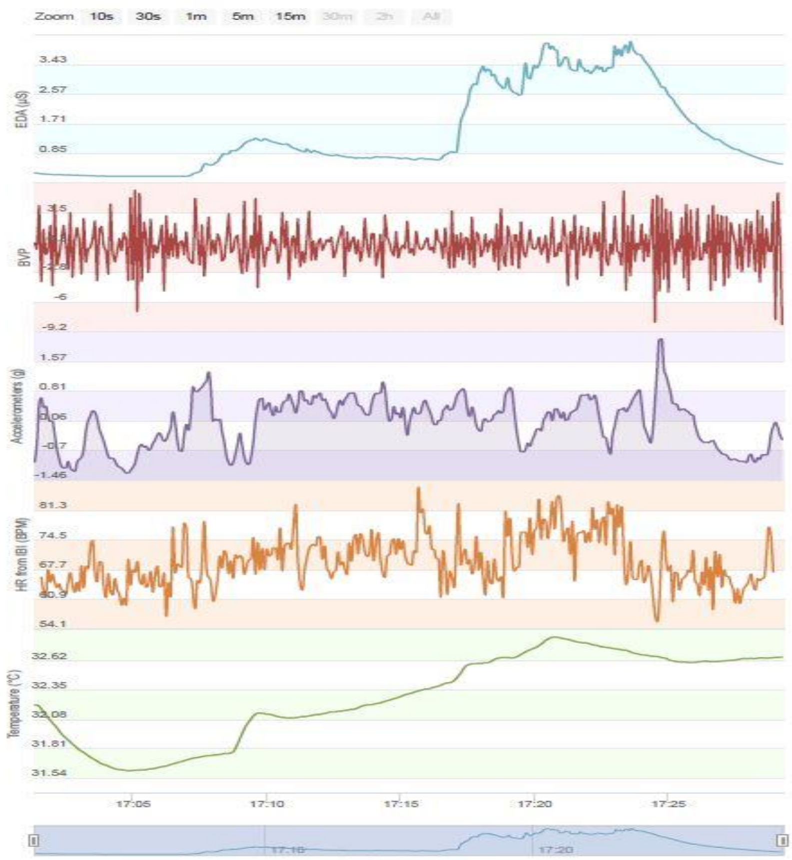


Fig. 7 Empatica data plots of one session.

Data is stored on the device during recording mode until a USB connection is made to a Mac or Windows PC running the E4 manager software (figure 8). The E4 manager saves the recorded sessions to the PC memory, clears the E4 memory, and resets the clock. It also uploads the session data to the E4 Connect servers for processing, viewing, and retrieval if an Internet connection is available.

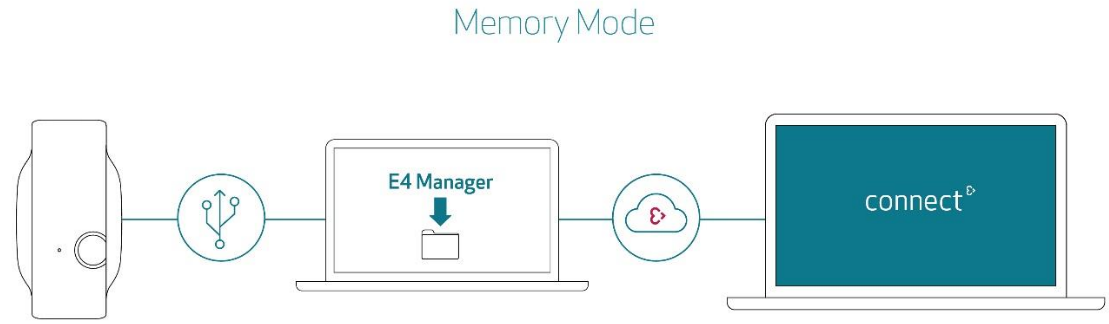


Fig. 8 Memory mode [42].

For this test, it was preferred to run the E4 in streaming mode (figure 9), which allows physiological data to be monitored from the device in real time via a Bluetooth® Low Energy connection. Once acquired, all data were downloaded to the PC in CSV format via the E4 Connect application and then converted to .txt files for the analysis [42].

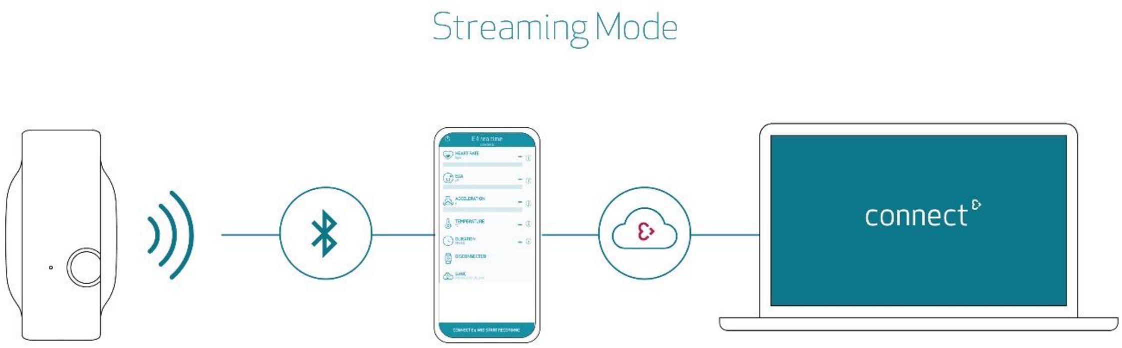


Fig. 9 Streaming mode [42].

4.3 Procedure

Data acquisition started with the subject being seated in a room. There were two rooms available, one for the participant used throughout the duration of the test and one for the performer, who had to leave the participant alone during the two relaxation phases and during speech preparation.

Initially, the subject was seated in a chair and instructed to wear the E4 wristband on the non-dominant hand. Throughout the acquisition, the hand remained immobile resting on a desk. The duration of the test was approximately 30 minutes. During these 30 minutes the first five and last five consisted of a relaxation phase.

After the first relaxation phase had elapsed, the performer entered the room with the participant and explained for one minute what he or she should do in the following 10 minutes. The performer then read the following script to the participant "This is the speech preparation portion of the task; you are to mentally prepare a five-minute speech describing why you would be a good candidate for your ideal job. Your speech will be videotaped. You have ten minutes to prepare, and your time begins now". After ten minutes, the performer returned to the room and listened and videotaped the participant during the speech part of the activity as he explained why he would be a good candidate for his ideal job. If the participant stopped speaking during the speech, he was allowed to remain silent for 20 seconds and if he did not resume speaking, he would be prompted to continue until the end of the five minutes. At the end of the vocal performance period, the following script was read to the participant, "During the final five-minute math portion of this task you will be asked to sequentially subtract the number 13 from 1022. You will verbally report your answers aloud and be asked to start over from 1022 if a mistake is made. Your time begins now". After this last task was completed, the participant was asked to relax for five minutes.

Throughout the test, the start and end time of each task was noted for each subject.

4.4 Data Analysis

Ledalab, a Matlab-based software, which analyzes skin conductance data and is also recommended on the Empatica website for signal processing, was used for data analysis. Initially, E4 files were downloaded and renamed for each subject. Ledalab only recognizes text files or Matlab files.

Therefore, considering that the only file we were interested in was the one referring to EDA, it was converted from .csv to .txt. Since, however, the text file also contained values such as the start period of the experiment and the sampling rate (4 Hz) in addition to the signal values expressed in microSiemens (μS), the first two lines were deleted. After that, the signal was loaded into Ledalab and was filtered with a low-pass Butterworth filter of order 1 with a cutoff frequency of 0.5 Hz.

First, the raw GSR signal was decomposed into its phasic component, more rapid and reactive, and tonic component, slower and constant, as shown in figure 10-11, using continuous decomposition analysis (CDA), and then the continuous phasic component containing the relevant features of the skin conductance signals was examined for further analysis.

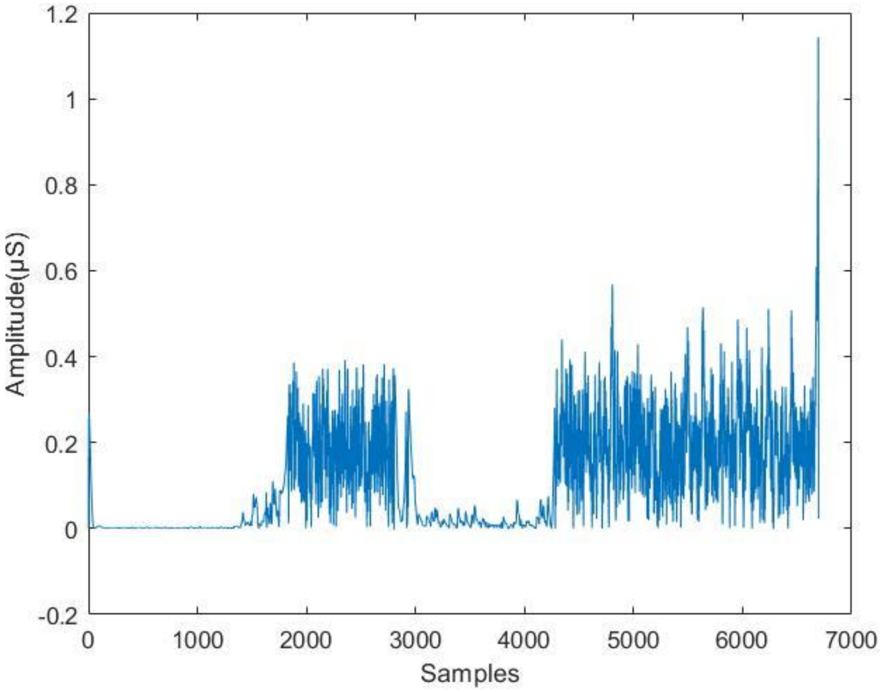


Fig. 10 Phasic component.

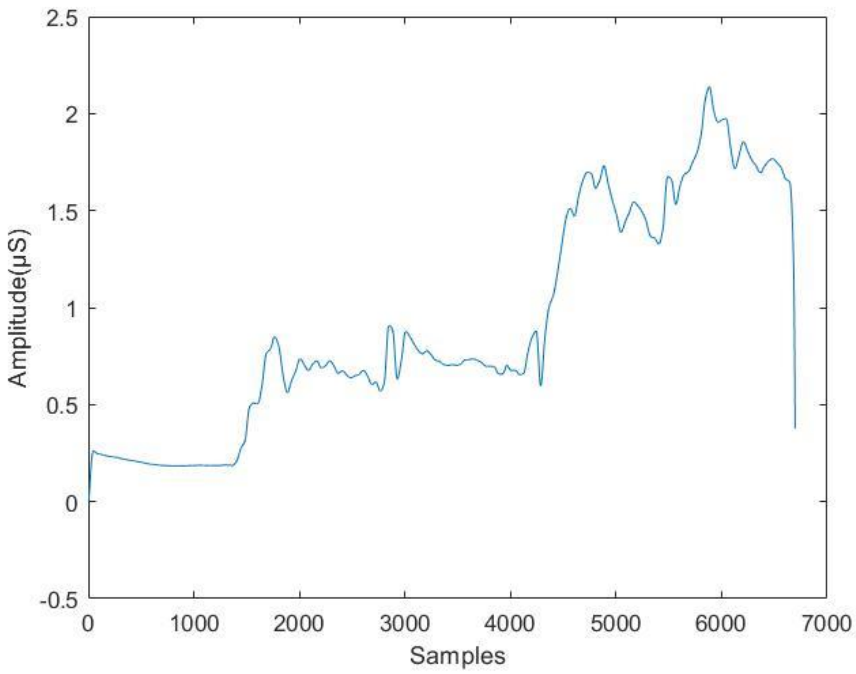


Fig. 11 Tonic component.

The skin conductance data are described by the superposition of successive skin conductance responses (SCRs). The process of estimating the actual responses of sympathetic activity in response to an external stimulus becomes arduous because of this property of SCRs. So, the deconvolution technique, which separates the skin conductance (SC) data into phasic and tonic continuous activity, overcomes this problem. Noise may be present in the tonic activity, indicating subject dependence. The phasic activity of the SC signal, on the other hand, is further studied because it contains the actual response to any event-related sympathetic activity, which is largely in the form of distinct bursts of spikes with a zero baseline. The phasic component is extracted in three steps: deconvolution of GSR data, calculation of tonic activity, and calculation of phasic activity as shown in figure 12.

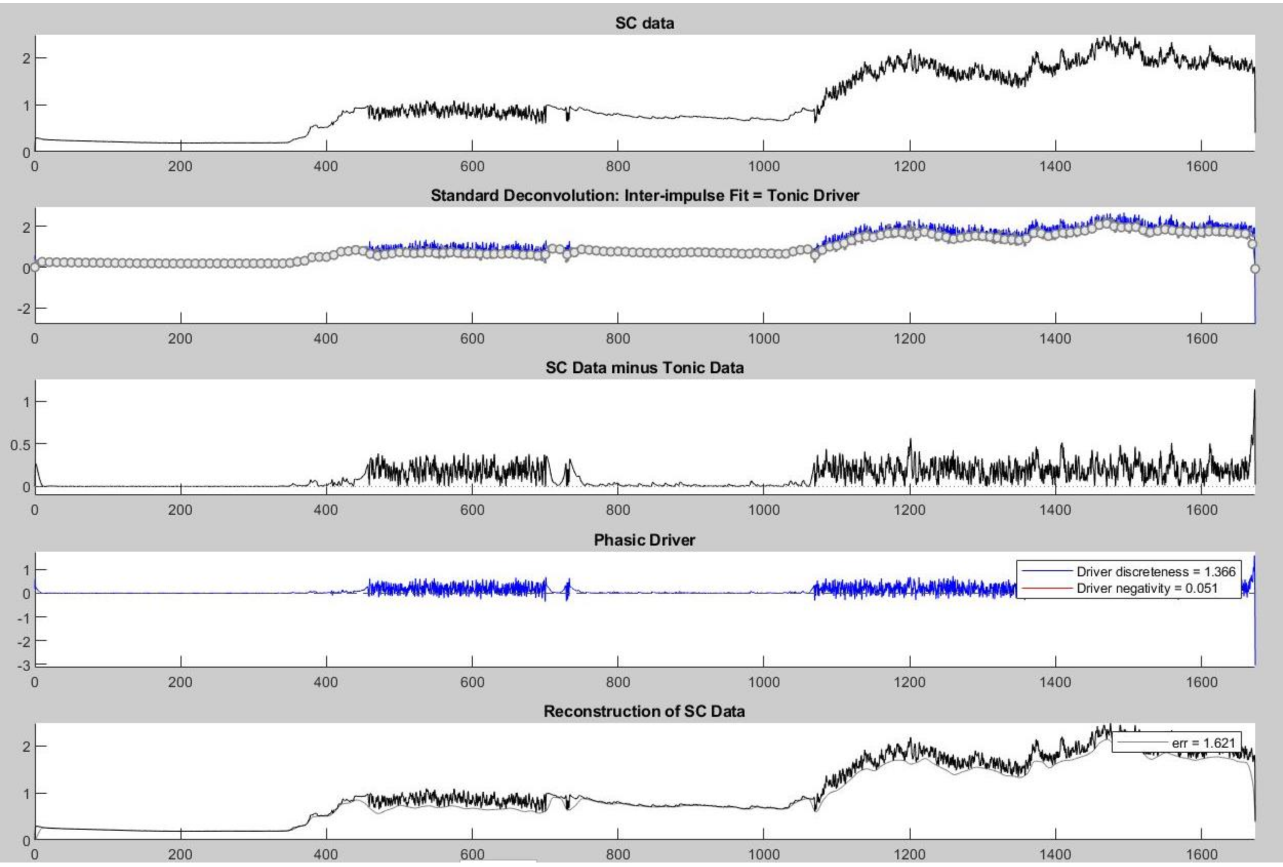


Fig. 12 Skin conductance signal; standard deconvolution to separate tonic data from phasic data; phasic components; reconstruction of skin conductance signal with both tonic and phasic component.

4.4.1 Features selection

When dealing with huge amounts of data (such as bio-signals over a long period of time), it's usually a good idea to use feature extraction and selection techniques. The term "feature extraction" refers to the process of reducing raw data to more detailed measurements. Computing signal features, for example using statistical methods, is an example of feature extraction. The goal is to reduce the data's dimensionality and make classification algorithms' work easier.

Models that work with identifiable features in the signals rather than raw data are easier to comprehend and more likely to be generalizable. After the features have been extracted, it is necessary to analyze which ones contain the most valuable information and to eliminate those that do not contribute to the model's improvement. Choosing a subset of the extracted features that offers a good prediction performance and a modest generalization error is referred to as feature selection [43].

To improve emotion pattern classification performance, the signal is processed to get all of the characteristics. This defines each signal segment and allows classification to distinguish between calm and stress.

Over the SCR component, several time-domain, frequency-domain, and morphological metrics are calculated. Usually the mean value (M), amplitude (A), standard deviation (SD), maximum peak value (MA), minimum peak value (MI), and dynamic range (DR), which is the ratio between maximum and minimum value, are the names of the most used temporal parameters over SCR.

So, after having performed the analysis of the signal in Ledalab, an algorithm was written in Matlab that analyzes the output of the CDA from which are extracted the data of the onset and the various amplitudes of the peaks.

Obviously, we could also scroll through the data and manually identify GSR peaks but, especially in case the recording session is very long, and the subjects are numerous, this could become a rather long and tedious process. Therefore, the algorithm was used to divide the signal into small one-minute segments by detecting the number of peaks, the average peak amplitude, the standard deviation and the maximum peak for each interval.

5. Results

In this study, the signals of eight subjects were analyzed noting a good response to stress during the last part of the experiment, in particular in the time range from about minute 18 to minute 27, in which the participant was subjected to a phase of more intense stress consisting in an arithmetic test as shown in figure 13-20. Sudden shifts in phasic activity above tonic activity are known as EDA peaks.

Fig. 13 EDA signal of the first subject.

Fig. 14 EDA signal of the second subject.

Fig. 15 EDA signal of the third subject.

Fig. 16 EDA signal of the fourth subject.

Fig. 17 EDA signal of the fifth subject.

Fig. 18 EDA signal of the sixth subject.

Fig. 19 EDA signal of the seventh subject.

Fig. 20 EDA signal of the eighth subject.

The CDA has as output values corresponding to onsets, which generally correspond to the point at which the GSR curve exceeds the minimum amplitude criterion (0.01 or 0.05 μS), and values corresponding to the amplitude of each peak. In addition, CDA allowed separation of the phasic and tonic components for each subject as shown in figure 21-28.

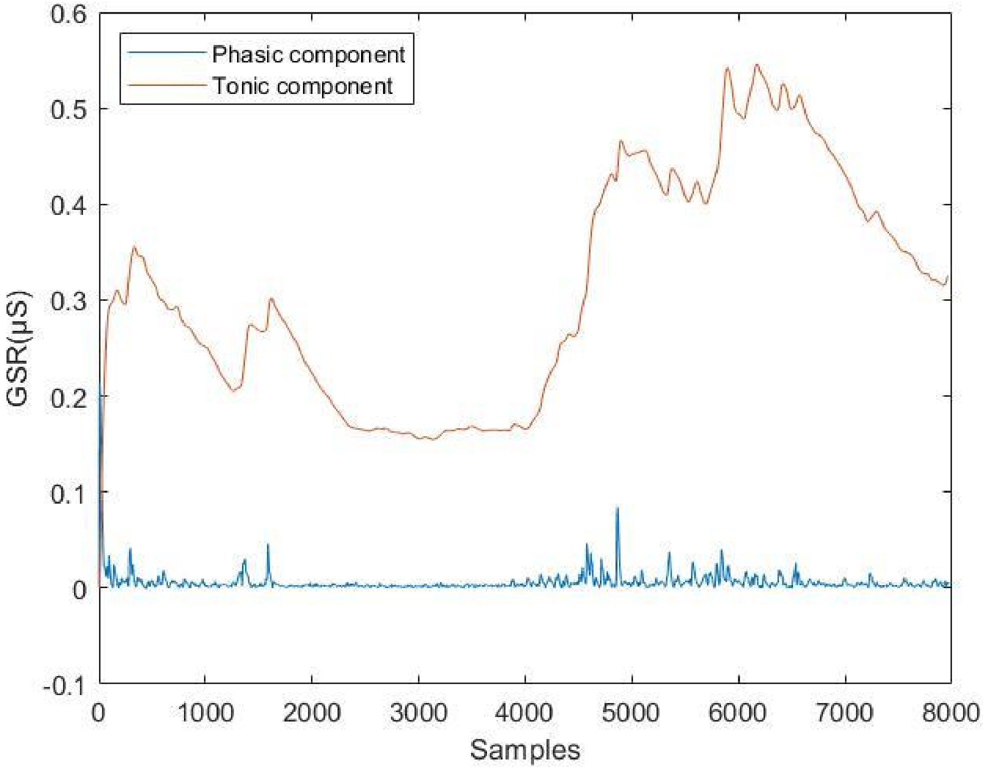


Fig. 21 Phasic and Tonic components of subject 1

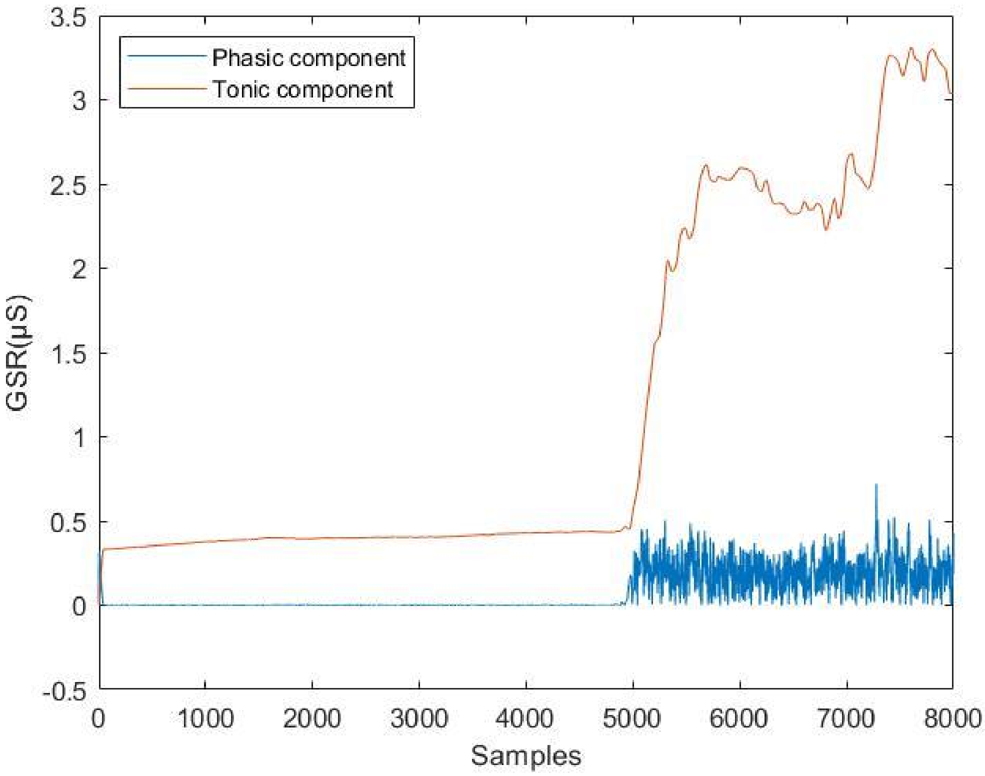


Fig. 22 Phasic and Tonic components of subject 2

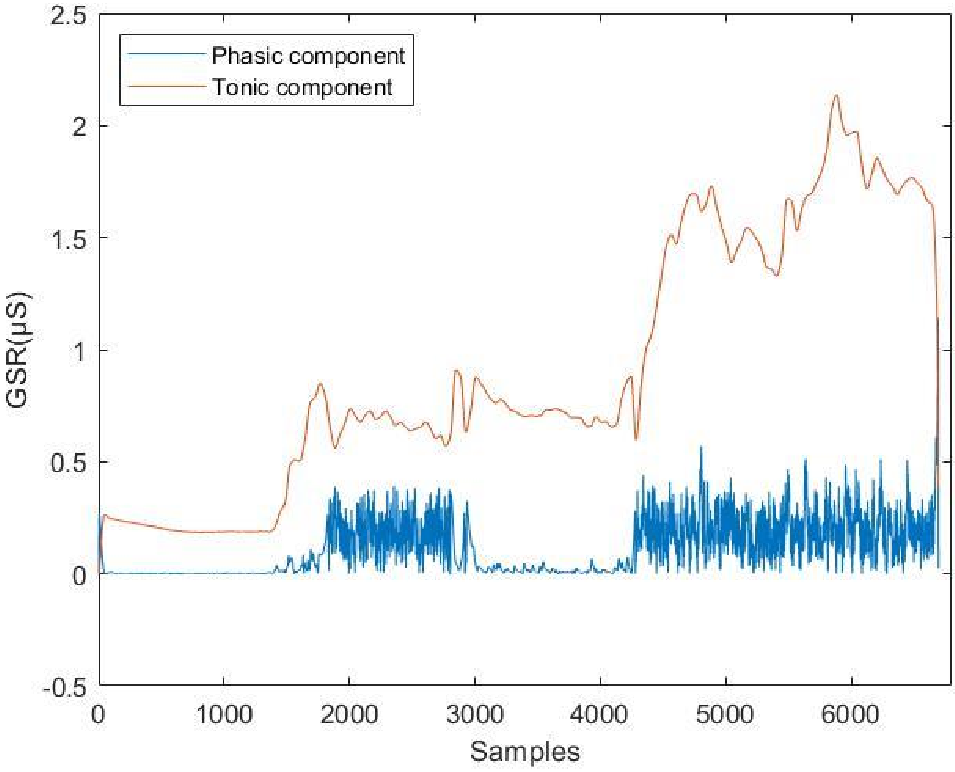


Fig. 23 Phasic and Tonic components of subject 3

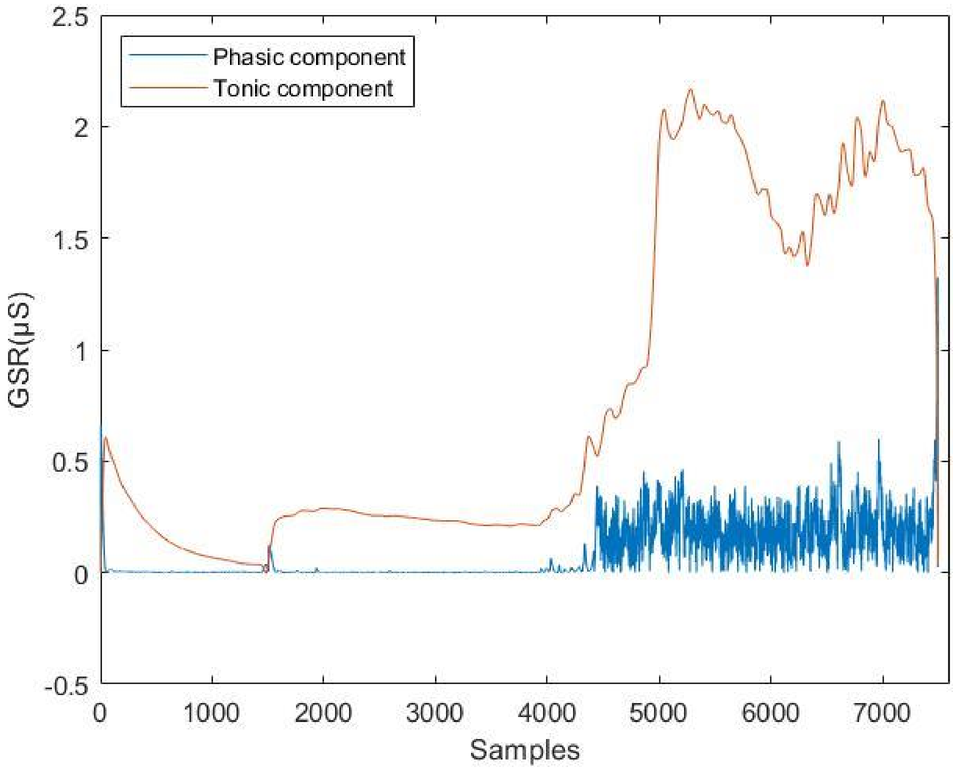
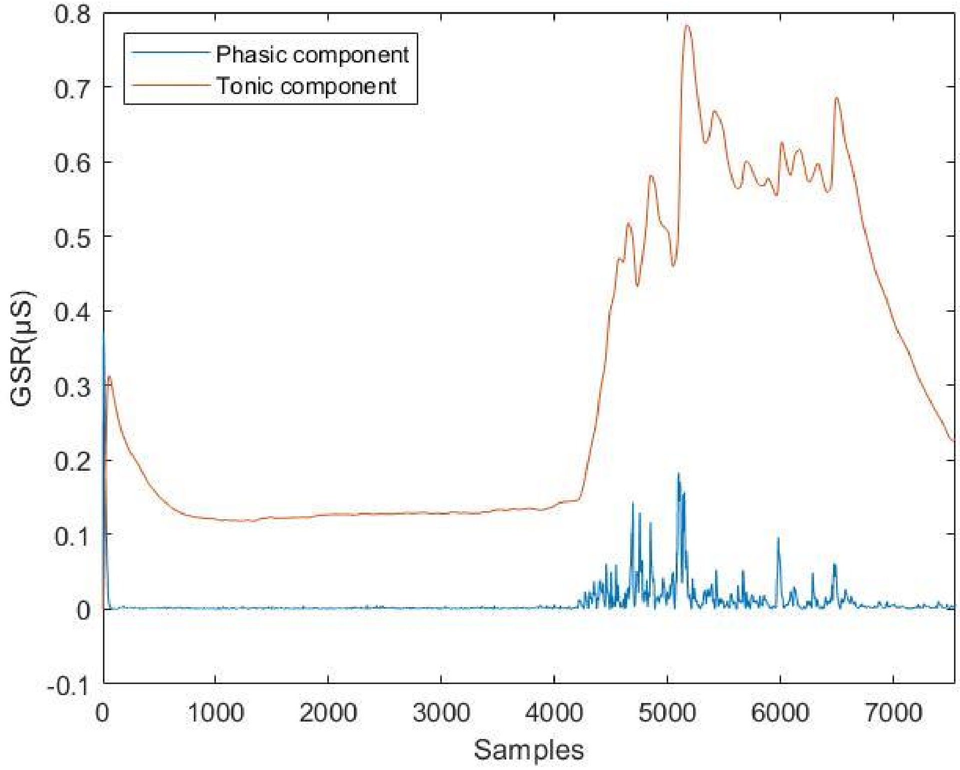


Fig. 24 Phasic and Tonic components of subject 4



[1]

Fig. 25 Phasic and Tonic components of subject 5

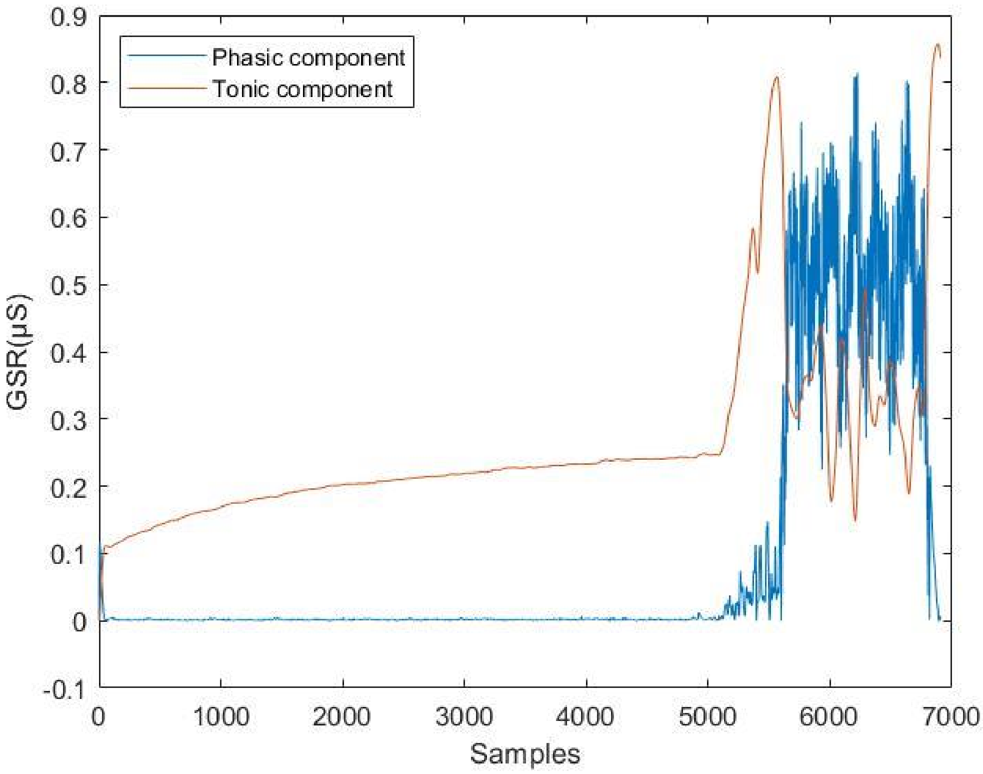


Fig. 26 Phasic and Tonic components of subject 6

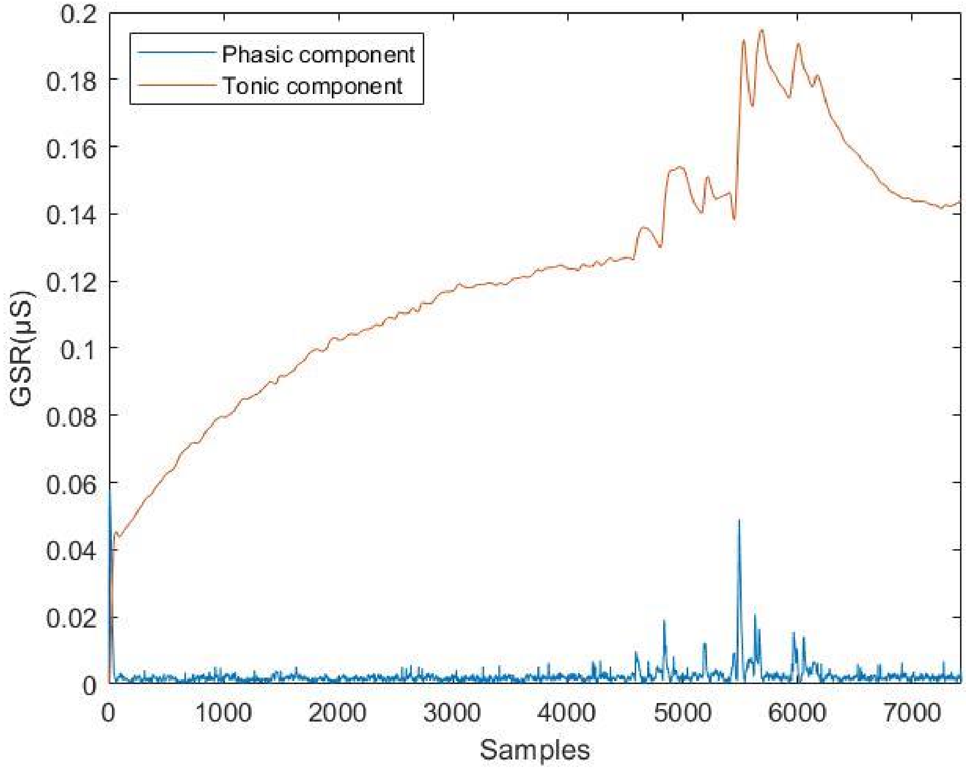


Fig. 27 Phasic and Tonic components of subject 7

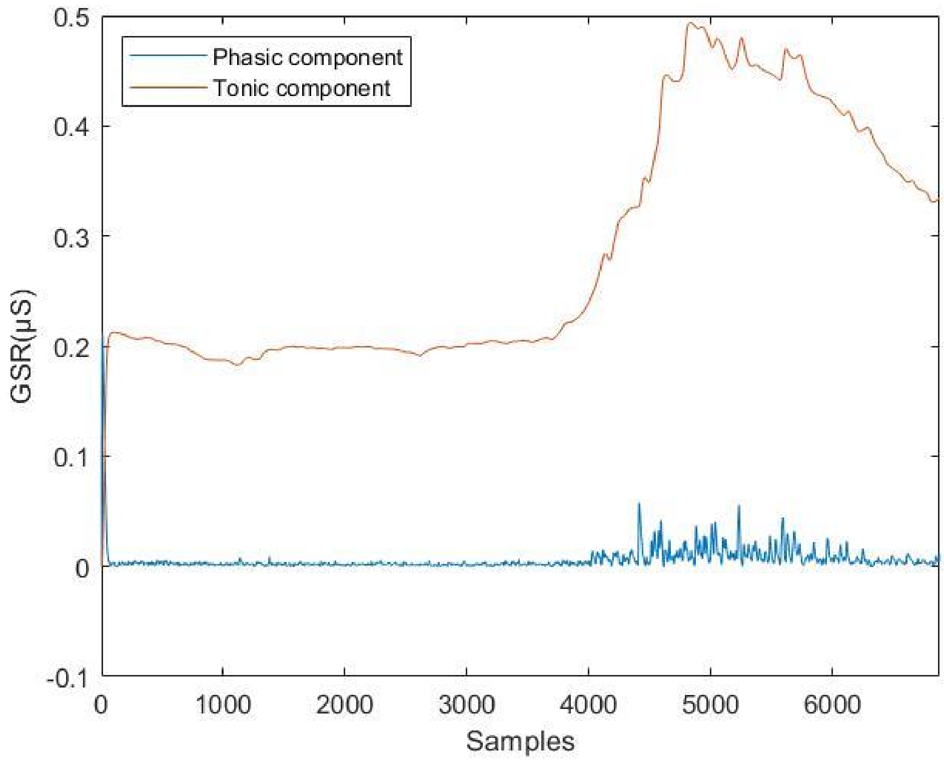


Fig. 28 Phasic and Tonic components of subject 8

From the phasic component, the number of peaks, the average peak amplitude, the standard deviation and the maximum peak for each interval were extracted. Table 1 shows the number of peaks for each one-minute time interval relative to each subject, and Table 2 shows the maximum amplitude reached in that specific time interval. In both tables it is possible to see how the peaks are more frequent and with a greater amplitude during the second phase of the experiment (arithmetic test). Moreover, it is possible to notice how some peaks are also recorded during the last phase of relaxation. This is due to the fact that, as also seen in literature, in the relaxation phase following an intense stimulus, during the first minutes, high peaks will always be recorded and then gradually return to a calm phase.

Sec.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
[0:60]	0	0	0	0	0	0	0	0
[60:120]	0	0	0	0	0	0	0	0
[120:180]	0	0	0	0	0	0	0	0
[180:240]	0	0	0	0	0	0	0	0
[240:300]	0	0	0	0	0	0	0	0
[300:360]	0	0	3	0	0	0	0	0
[360:420]	0	0	19	6	0	0	0	0
[420:480]	0	0	25	0	0	0	0	0
[480:540]	0	0	41	1	0	0	0	0
[540:600]	0	0	42	0	0	0	0	0
[600:660]	0	0	41	0	0	0	0	0
[660:720]	0	0	28	0	0	0	0	0
[720:780]	0	0	22	0	0	0	0	0
[780:840]	0	0	14	0	0	0	0	0
[840:900]	0	0	16	0	0	0	0	0
[900:960]	0	0	8	0	0	0	0	0
[960:1020]	1	0	9	5	0	0	0	1
[1020:1080]	2	0	18	12	3	0	0	2
[1080:1140]	6	0	38	23	14	0	0	6
[1140:1200]	7	0	40	36	17	0	0	7
[1200:1260]	9	12	38	38	18	1	1	9
[1260:1320]	8	37	40	34	14	13	0	8
[1320:1380]	5	40	42	39	10	24	2	5
[1380:1440]	12	36	36	40	6	37	2	12
[1440:1500]	3	33	38	38	7	41	1	3
[1500:1560]	2	37	40	36	4	38	-	2
[1560:1620]	0	43	40	40	7	40	-	0
[1620:1680]	0	41	39	41	5	39	-	0
[1680:1740]	1	36	-	38	-	23	-	1
[1740:1800]	-	38	-	43	-	-	-	-
[1800:1860]	-	40	-	41	-	-	-	-
[1860:1920]	-	36	-	-	-	-	-	-
[1920:1980]	-	40	-	-	-	-	-	-

Table 1. Number of peaks for each interval of 60 seconds for every subject (S_1 to S_8).

Sec.	**S_1**	**S_2**	**S_3**	**S_4**	**S_5**	**S_6**	**S_7**	S_8
[0:60]	0	0	0	0	0	0	0	0
[60:120]	0	0	0	0	0	0	0	0
[120:180]	0	0	0	0	0	0	0	0
[180:240]	0	0	0	0	0	0	0	0
[240:300]	0	0	0	0	0	0	0	0
[300:360]	0	0	0.030	0	0	0	0	0
[360:420]	0	0	0.070	0.120	0	0	0	0
[420:480]	0	0	0.330	0	0	0	0	0
[480:540]	0	0	0.350	0.020	0	0	0	0
[540:600]	0	0	0.350	0	0	0	0	0
[600:660]	0	0	0.350	0	0	0	0	0
[660:720]	0	0	0.350	0	0	0	0	0
[720:780]	0	0	0.300	0	0	0	0	0
[780:840]	0	0	0.050	0	0	0	0	0
[840:900]	0	0	0.050	0	0	0	0	0
[900:960]	0	0	0.020	0	0	0	0	0
[960:1020]	0.010	0	0.060	0.060	0	0	0	0.010
[1020:1080]	0.010	0	0.290	0.040	0.020	0	0	0.010
[1080:1140]	0.060	0	0.390	0.380	0.060	0	0	0.060
[1140:1200]	0.030	0	0.350	0.330	0.120	0	0	0.030
[1200:1260]	0.040	0.310	0.350	0.450	0.110	0.010	0.010	0.040
[1260:1320]	0.030	0.420	0.320	0.390	0.160	0.050	0	0.030
[1320:1380]	0.020	0.460	0.410	0.370	0.050	0.140	0.040	0.020
[1380:1440]	0.030	0.430	0.430	0.350	0.050	0.530	0.020	0.030
[1440:1500]	0.020	0.380	0.430	0.320	0.080	0.520	0.010	0.020
[1500:1560]	0.020	0.330	0.400	0.350	0.030	0.600	-	0.020
[1560:1620]	0	0.310	0.420	0.350	0.050	0.480	-	0
[1620:1680]	0	0.330	0.930	0.540	0.040	0.650	-	0
[1680:1740]	0.010	0.410	-	0.440	-	0.480	-	0.010
[1740:1800]	-	0.390	-	0.390	-	-	-	-
[1800:1860]	-	0.630	-	0.300	-	-	-	-
[1860:1920]	-	0.430	-	-	-	-	-	-
[1920:1980]	-	0.500	-	-	-	-	-	-

Table 1. Maximum amplitude (μS) for each interval of 60 seconds for every subject (S_1 to S_8).

For further analysis, a GSR aggregation was performed based on binarization of the signal. Initially, the value 1 ("true") was assigned to intervals that contained at least one GSR peak and the value 0 ("false") was assigned to intervals that contained no GSR peak.

Thus, instead of the actual amplitudes of the GSR peaks, the binary values 0 and 1 were used. After that, the binary scores were summed for each interval across all the participants.

For example, if there were 10 subjects surveyed and all had at least one GSR peak in a certain interval, the aggregate value for this interval would be 10. Otherwise, if none of the respondents had a GSR peak in the interval, the aggregate value for this interval would have been 0.

In the case under consideration, since GSR data were collected from 8 subjects, a value from 0 to 8 was associated for each interval. The resulting graph (figure 29) shows that almost all subjects had at least one peak during the mathematical test phase, thus resulting as the period of greatest stress.

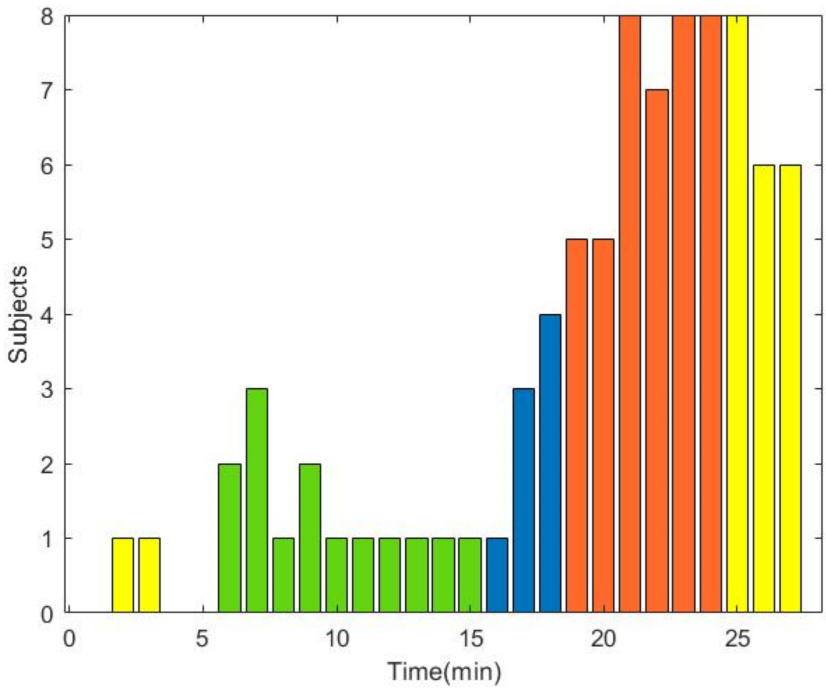


Fig. 29 Stress trend. Relax phase (yellow), speech preparation (green), speech performance (blue), aritmetical task (orange).

6. Conclusion

The purpose of this study is to monitor and assess stress through the galvanic skin response using the smart watch Empatica E4. Specifically, the aim was to demonstrate the possibility of monitoring the stress condition through changes in the electrodermal activity of the skin. The experiment was conducted on eight adult subjects undergoing different phases of stress for about 30 minutes. During the first and the last five minutes of the test, the participants were subjected to a relaxation phase and during the rest of the time they had to prepare a speech and expose it in front of the examiner followed then by an arithmetic test. The EDA signals extracted from Empatica E4 were then analyzed in Ledalab and were filtered with a low-pass Butterworth filter of order 1 with a cutoff frequency of 0.5 Hz. This choice was due to the pre-processing performed in the studies taken from the literature in which the low-pass filter was recommended to eliminate any kind of high frequency noise components. The signals were then divided into windows of 60 seconds through an algorithm implemented in Matlab thanks to which the most important features such as the number of peaks, the average amplitude, the standard deviation and the maximum of the peaks were then extracted. Analyzing all these data, by means of a statistical analysis, it was possible to highlight how the highest number of peaks among all subjects was highlighted during the phase of greatest stress, that is during the arithmetic test. The initial hypothesis, in fact, was that after a phase of relaxation, one of moderate stress and one of more intense stress there should have been a greater number of peaks and greater amplitudes during the last phase and so it was. So, the device used was very effective in detecting stress during a laboratory experiment conducted on different subjects but especially in discriminating a phase of relaxation from a phase of intense stress. The significant difference between the value of the characteristics obtained before and after the induction of stress confirms that the protocol used was also efficient in achieving the objective of this study. On the other hand, however, all these tests were carried out in laboratory environments and therefore in environments where each subject could control every action and avoid artifacts during signal recording. So, the next step, starting from this preliminary analysis, will be to apply what has been done so far in real life moments and more specifically in a working environment.

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