

**STRESS LEVEL DETECTION USING MACHINE LEARNING**

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Review of Stress Detection Methods Using Wearable Sensors

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**ABSTRACT** Stress is a significant factor that affects well-being and health. Factors that trigger stress include work, social interactions, and economic and environmental factors. Stress may cause lower labor productivity, physical and mental health problems, and malfunctions in all social aspects of life. Psychosomatic health can be improved if proper stress detection mechanisms are present in daily life and stress reduction methods can occur. Wearable sensors are currently used in many commercial and scientific applications in a non-destructive or annoying manner. These devices are used in daily routines. In this paper, a comprehensive review of the latest literature and developments in stress detection methods is



presented through extensive and holistic research on stress response, both at the level of the autonomic nervous system (ANS) and hypothalamic-pituitary-adrenal axis (HPA). This study focused on the exploitation of various methods, technologies, and data analysis systems to understand stress in a multifaceted and comprehensive manner. Various stress-related factors are presented along with biological signal measurements, and physical secretions or biomarkers are primarily used for stress detection. Furthermore, the manner in which body movement and posture measurements may be related to stress was investigated, together with speech and hand tremors. Various stress-detection technologies have been analyzed, and existing data analysis methods that can be applied to stress-detection systems have been highlighted. This review serves as a reference and guideline for exploring this area of interest, identifying research opportunities, and offering ideas, options, and suggestions for optimized solutions regarding future applications and research.

**INDEX TERMS** Stress analysis, stress detection, stress response, wearable sensors.

1. **INTRODUCTION**

Stress in modern days is considered not only an important factor of well-being but also a factor of basic health. Stress has been described as a “hidden epidemic” of modern times at least since 2002 [1].

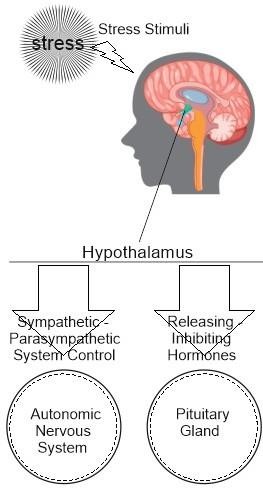
The economic impact of stress is considered to be huge, especially when discussing work stress, where it is estimated that approximately $300 billion is spent annually in the US [2].

The World Health Organization estimates that every dollar spent on fighting depression and anxiety pays four times as much [3].

American psychologist Walter Cannon (October 19, 1871 – October 1, 1945) defined stress as any deviation from homeostasis [4]. Homeostasis, the steady physiological state of the living human body, was also proposed by him. Critical parameters, such as temperature, heartbeat, and blood pressure, can be measured within a certain limit using biological sensors.

Many professional, social, and personal problems as well as difficult situations are caused or aggravated by stress. Labor productivity decreases significantly under conditions of stress [5], depression, and some psychogenic and pathological diseases as well as in the sexual ability of both men and women [6].

To solve this problem, it is important to detect their presence first. Thus, the causes of the problem (stress), place, and time can be identified, treated, or mitigated. However, stress, in general, is a natural physiological defensive-compensatory mechanism in the body that creates problems only when it is uncontrollable, beyond certain limits, and unmanageable. It should also be mentioned that sometimes controlled stress is deliberately caused (e.g., intensive intermittent exercise, cold, heat) by the person, so that he later receives the beneficial, soothing, and healing interventions of the brain to the body (hormone secretions, endorphins).



**FIGURE 1. Stress response: Role of the hypothalamus (source: authors).**

Two main mechanisms respond to stress stimuli and are coordinated by the hypothalamus [7]. The hypothalamus is a part of the brain located below the thalamus. It is also associated with the nervous and endocrine systems (Fig. 1). In response to stress, it can trigger (a) the sympathetic nervous system (SNS), which is a part of the autonomic nervous system (ANS), and (b) hormone production. SNS can control the so-called “fight-or-flight” response and, for instance, can increase heart rate, blood pressure, and eye pupil enlargement. Additionally, the hypothalamus can provoke the production of hormones through the hypothalamus-pituitary-adrenal (HPA) axis to counter stress. In contrast, under stress recession conditions, the hypothalamus can trigger the parasympathetic nervous system (PNS), which is a part of the ANS. The PNS predominates in the so-called “rest and digest” conditions, thus relaxing the body, and at the HPA

axis level, the hypothalamus inhibits stress hormone production.

Historically, the polygraph (known as the lie detector test) measures and monitors the breathing rate, perspiration, skin conductivity, blood pressure, and pulse rate [8]. Polygraphs can be considered an ancestor of stress-measurement systems. The classical, reliable, and accurate method for measuring and quantifying psychological stress was developed in 1983 by S. COHEN et al. (Journal of Health and Social Behavior, 1983) and is a questionnaire known as the Perceived Stress Scale (PSS) [9]. There were three versions of the questionnaire. The original questionnaire used was the PSS-14. Subsequently, shorter versions, such as the PSS-4 and PSS-10, were introduced [10]. Technology has advanced, and stress can be measured (“automatically”), even with wearable devices.

The modern trend of using mobile devices, such as laptops, tablets, or smartphones, and the continuous development of technology in this field, with increasingly powerful and smaller processors and chips that consume less energy but also optimize batteries (in terms of capacity, charging speed, and charge cycle), are beneficial for the development of wearable stress detection devices.

Miniaturized semiconductor devices appear more and more into commercial electronic devices, aided by new microfabrication technologies [11]. These technologies allow the development of small-sized wearable devices that can assist in stress detection [12]–[14].

Wearable sensors are often used in simple and practical applications. These sensors are friendly to the person being investigated for stress, have low complexity, and do not require cumbersome medical protocols. They can be easily and safely applied to almost any person or environment, including daily life, hobbies, or work.

Wearable devices that can be worn almost everywhere are an attractive way to monitor stress. Watches, wristbands, rings, bracelets, necklaces, and eyeglasses can be utilized to sense stress-associated biosignals. Furthermore, straps (chest straps), patches, lenses, and other devices that may be less friendly but still practical can be used for this purpose.

Smartwatches are wearable devices that have evolved significantly in the last decade. Commercially available smartwatches not only show time, month, and year but also have many other modern features, such as Internet connectivity, various applications support, and integrated sensors for wellness. These sensors can be defined as human biomarkers that can measure the heart rate, temperature, oxygen saturation in the blood, and blood pressure. These measurements are sometimes accurate and certified by the US Food and Drug Administration (FDA). A thorough investigation of the latest (by priority) developments and literature concerning stress detection, response, and measurement was conducted using a holistic

approach. Common and uncommon biomarkers, sensors, devices, methods, and technologies have been explored. Research has also been conducted at another (medical) level, for example, in human secretions (related to the stress substances of these secretions), hand tremors, body posture, eye dynamics, and sensors that respond to and measure all of these elements. This review is a synthesis- correlating product of such information. Furthermore, the prevailing methods of data analysis and classification as well as their transfer and transmission methods are highlighted. Several sources have been used to prove various cases and points. As for essential concepts and historical stages in the study of stress, older articles, books with significant impacts, and sources of sources were also used. Therefore, a broader, more complete, and up-to-date view with various options, tools, and methods was provided. This review intends to identify innovative, unexplored, and underexplored areas in this field that can optimize stress detection and measurement and introduce new ideas and research horizons. Suggestions, directions, and estimations are also provided.

The remainder of this paper is organized as follows. In the next section, various stress-related factors that could be used for stress detection are discussed. Section III presents a detailed description of commercially and scientifically available stress detection technologies, and various body measurement points and methodologies are described. The manner in which these measurements were collected from a networking perspective is presented in Section IV. Various data analysis methods are described in Section V. A discussion and overall conclusions are provided in Sections VI and VII, together with a general proposal for the most preferable solution.

## STRESS RELATED FACTORS

* 1. ***BIOLOGICAL SIGNAL MEASUREMENTS***

Detecting stress in real time and analyzing biosignals from wearable devices in everyday life – routine–are challenging tasks. This task becomes easier in controlled environments (for example, in medical laboratories), especially when blood analysis is possible together with other specialized laboratory methods. On the other hand side, in the last years, out-of-lab detection of stress is also of equal importance and the technological advances of wearables assisting in detecting stress are enormous [15].

The autonomic nervous system (ANS) responds to stress [16], [17]. It has also been scientifically proven that the ANS regulates the functions of the cardiovascular system, skin, respiration, eye (pupil size, eye blinking, and eye movement), and many other organs.

A variety of biosignals from the human body, which are controlled by the ANS and therefore affected by stressful conditions, can be obtained through wearable devices [18]– [20]. The most commonly used biological signals originate

from the heart and skin, and are probably the most important. Individual measurements or a combination of several measurements may detect and expose stressful situations.

1. HEART RATE (HR)

HR increases when the body requires either more oxygen or the elimination of carbon dioxide. Acute stress responses increase the HR.

Heart rate variability (HRV) refers to slight time fluctuations between heartbeats and is generally not considered an arrhythmia [21]. The normal heart beating is called “sinus rhythm”, and if the variability between heartbeats is greater than 0.12 s, then this event is called “sinus arrhythmia”. Breathing usually induces sinus arrhythmia; thus, HRV can be used to measure breathing rate [22]. The term R-R interval or inter-beat interval (IBI) is the time (measured in milliseconds) between heartbeats.

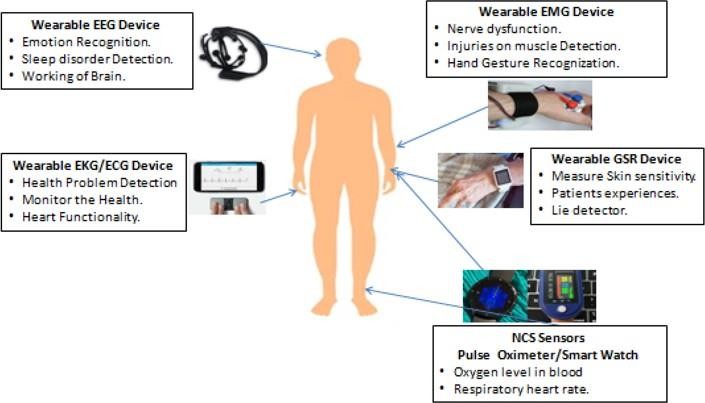
The sympathetic and parasympathetic systems are parts of the autonomic nervous system ANS [23]. The ANS is a subconscious mechanism of the brain and the nervous system that controls the heart. The sympathetic nervous system induces a faster heartbeat and a higher blood pressure. This, in turn, provides more oxygen to the body to cope with stressors (e.g., fear, danger, and rush). Simultaneously, the parasympathetic system attempts to restore all of the above to normal conditions (reducing blood pressure and heart rate) after the stressor or initial stimulation has gone or been reduced.

Electrical changes (voltage) are observed in the heart muscle, and a graphic representation of these electric signals represents an electrocardiogram (ECG) [24]. ECG, HR, and HRV were easily measured. ECG is explained in more detail as an electrical technology for stress detection in Section III of this paper.

The heart produces seismic and ballistic effects. Wearable wrist devices with accelerometers (e.g., triaxial microelectromechanical (MEMS) accelerometers) and electromechanical film (EMFi) sensors can detect these effects [25]. Seismocardiography (SCG) and ballistocardiography (BCG) [26] are methods reported in the literature that can measure HR and breathing rate [27] using ballistic forces and vibrations of the heart.

Finally, heart rate can be measured optically using photoplethysmography (PPG). This method measures blood volume pulse (BVP). Recently, commercially available wearable devices have been offering reliable (with FDA clearance) and continuous measurements of wrist heart rate using the PPG method.



**FIGURE 2. Various wearable biosignal devices and utilities can assist with stress detection and analysis [28].**

1. TEMPERATURE

Temperature (usually in association with others) is a physiological measurement used for stress detection [29]– [31], and skin temperature may reveal the intensity of acute stress [32]. Skin temperature is usually measured rather than inner body temperature using wearable sensors for usability reasons. Most measurements are taken on the wrist [33], [34] (wearable devices such as watches or watch-style devices), fingers, or the main core of the body skin ( electronic patches [30], specialized belts with integrated sensors, straps, etc.). Some wearable thermometers are equipped with thermistors, others with embedded liquid crystal strips, and others use infrared (IR) emission technology [35]. High-precision measurements can be recorded using all the employed technologies.

Skin temperature measurement via the wrist is mostly performed using a contact thermistor or a contactless IR thermometer. Normal skin temperature is usually approximately 33 °C to 35 °C, which is lower than the usual normal body temperature (33.6 °C to 37 °C).

Changes in body temperature may indicate disease, abnormalities, or possibly stressful conditions.

1. BLOOD OXYGEN SATURATION (SPO2)

A large percentage of oxygen is transported through the red blood cells (hemoglobin). Hb oxygen saturation can be measured by several methods. Usually, this measurement is useful for detecting hypoxia (poor oxygenation of the body, particularly the brain) [36]. It is a measurement that medical personnel and lay people use for diagnosis or preventive treatment. Recently, coronavirus disease, also known as Covid-19, sometimes has the effect of "silent" hypoxia, and this measurement is now widely known in the medical field. Wristwatches can continuously and smartphones can instantly measure blood oxygen saturation via red and infrared reflection-led light [37]. In the case of stress, some possible variations in this measurement were investigated and their correlation with it (stress).

**FIGURE 3. Blood oxygen saturation, heart rate, and blood pressure were measured using a medical wristwatch via photoplethysmography and artificial intelligence (AI) [38].**

Stress and anxiety alter the respiratory rate, thereby altering oxygen saturation in the blood [39]; hence, there is a correlation between the breathing rate and blood oxygen saturation.

There are three methods for measuring blood oxygen saturation: wearable fingertip pulse oximetry, transmission photoplethysmography (T-PPG), and reflectance photoplethysmography (R-PPG) [40]. Only a few wearable devices have clinical grade accuracy of SpO2 [41] with FDA or other medical organization approval.

1. BLOOD PRESSURE (BP)

Blood pressure (BP) measurements are related to the heart and arteries. As blood flows through the arteries, pressure is produced at their walls. The systolic and diastolic pressures were measured. BP reactivity, along with other pathophysiological reactions, is repeatedly associated with stress [42], [43]. However, many other physical activities can increase BP, indicating that it is not a simple task to associate BP with stress individually.

Some wearable wrist-based devices measure BP, and only a few are clinically accurate and approved by the FDA [44], the majority of which are not sufficiently accurate [45]. Accurate BP measurement is related to stress and critical for the prognosis of hypertension. Hypertension is considered the most common risk factor for cardiovascular diseases [46]. Ballistocardiography and the time taken for the systolic pressure wave to travel from the aortic valve to a peripheral site, called the pulse transit time (PTT), offer an opportunity to estimate cuffless blood pressure monitoring [47] with the synergy of photoplethysmography (PPG) and/or electrocardiography (ECG) [45]. Cuffless-estimated BP based on bioimpedance sensors is also expected to be commercially available [48].

**FIGURE 4. Real-time blood pressure measurement using a commercially available wristwatch [49].**

1. BRAIN ACTIVITY

The brain regulates the autonomic nervous system (ANS) through a region of the brain called the hypothalamus. The ANS, specifically the sympathetic and parasympathetic systems, responds to emotions, cognition, and mental stress. The hypothalamus controls many vital functions such as heart rate, body temperature, thirst, and sleep and responds to an ANS arousal alert with hypothalamic hormones to bring about body balance (homeostasis) [50].

Neurons in the cerebral cortex produce electricity (current ions) or voltage fluctuations. Wearable devices are used in scientific studies and fitted to the head (scalp) to measure and record this activity [51]. However, these devices are difficult to wear and can be worn widely in any environment in a manner similar to devices on the wrist, chest, arm, and skin. Nevertheless, they are becoming increasingly attractive (lighter, with less volume, and easier to apply), particularly at home and in the office.

Near-infrared (NIR) light emitted (from a device) to the outer cortex of the brain is absorbed, resulting in changes in quantity upon receiving a stimulus. Thus, NIR methods or devices on the scalp can be used to study these functional signals [52]. Wearable devices can be used for NIR spectroscopy [53]. Evaluation, detection, and measurement of stress via brain activity [54] as the sole factor – parameter

1. or in combination with other activities such as biosignals
2. of the human body (e.g., skin and heart).
3. DERMAL AND MUSCLE ACTIVITY

The skin is the largest in the human body. The skin covers the outer part of the body. Among many other things, the skin regulates body temperature with a cooling system commonly known as sweating. Sweating is controlled and triggered by the sympathetic nervous system and alters the conductivity and humidity of the skin surface [57]. Electrodermal activity (EDA) is the ability of the skin to vary its electrical conductance and electrical characteristics. EDA is frequently used in psychophysiological evaluations [58] and stress. The skin conductance (SC) and skin potential (SP) response peak time difference between these signals (SC and SP) during relaxation and stress (or an unexpected cause) [59]. The skin is directly affected by the human sympathetic system, and no parasympathetic action directly affects the skin; thus, it is an ideal part of the human body to observe the action, stimulus, and effect of the sympathetic system.

The galvanic skin response (GSR), which is part of the EDA, detects changes and fluctuations in the electrical response of the skin sweat glands. GSR are formed by the synthesis of phasic and tonic components [60]. The differences between tonic and phasic are in terms of time and abrupt variations. The phasic part exhibited sharp outbursts and short responses (a few seconds), whereas the tonic part was typically slower (seconds to minutes) and smoother.

Muscle cells produce electric potentials when they are neurologically or electrically activated. Electromyography (EMG) can measure this activity using EMG electrodes on a muscle (e.g., trapezius muscle). The relationship between EMG activity and increased activity after a stimulus or stressor in some muscles has been evaluated and investigated. Usually, a combination of measurements, such as EDA (GSR), EMG, electrocardiography (ECG), EMG [61], or other combinations, are used to determine, evaluate, or investigate stress responses.

1. RESPIRATION RATE AND VOLUME

Respiratory breathing involves the inhalation and exhalation of air to and from the lungs. Respiration rate is the number of breaths per unit of time, typically per minute. In stressful situations, this rate changes [62].

Breathing rate can be associated with heart rate. Specifically, it is associated with heart rate variability [63]. Breathing rate can also be measured using electrodes [64] (through electrical fluctuations and impedance [65]), radio- frequency sensors [66], piezoelectric sensors [67], [68], and strain sensors [69]. Currently, several commercially available wearable devices are in use.

Measuring respiratory rate using wearable devices is relatively easy, and there is a plethora of wearable devices that perform such tasks. Measuring breath volume is more difficult, but steps are being taken in this direction [66], [69]. Usually, under stress conditions, a fast respiration rate induces shallow breathing [70].

Breathing can have the opposite effect [71]. Control of the respiration rate and depth (volume) can reduce blood pressure [72] and heart rate variability [73], which can lead to relaxation and stress reduction by enabling the parasympathetic system (vagus nerve) [74].

1. EYE DYNAMICS

The pupillary dilator muscle of the iris is controlled by sympathetic and parasympathetic systems. The pupil responds (a) to light (pupil light response (PLR)), (b) to the near fixation-near reflex (pupil near response (PNR)), and there is another response (c) to the pupil psychosensory response (PPR) related to cognitive activity [75]. The last response of the pupil is related to mind effort or mind processing load after something has captured attention or strong emotion and causes pupil dilation through the sympathetic system.

The sympathetic system responds to stress and induces pupil dilation, whereas the parasympathetic system stimulation causes pupil constriction [76]. Therefore,

pupillometry is another possible method to detect and evaluate stress.

Eye blinking [54] or eye closure is another additional measurement that uses an eye tracker (more often, specialized glasses are used) that can be evaluated or co- evaluated for stress detection [77]. In addition, eye gaze [78], eye movement (rapid movements), and eye activity, in general [20], [79].



**FIGURE 5. Eye tracker glasses for stress detection with cameras for eye pupil diameter and blinking frequency observation, and other sensors [80].**

However, eye measurements require specialized and expensive devices. These measurements are ideal for individuals who can wear helmets at work, or during other activities. For example, eye dynamics measurements can be performed on pilots (airplanes, racing cars) [81] and truck drivers [20], so they will not fall asleep, their attention is low, they have a high emotional workload, etc. Novel devices such as glasses with eye trackers, are now easier to implement and are used in a number of applications.

* 1. ***PHYSICAL SECRETIONS - BIOMARKERS***

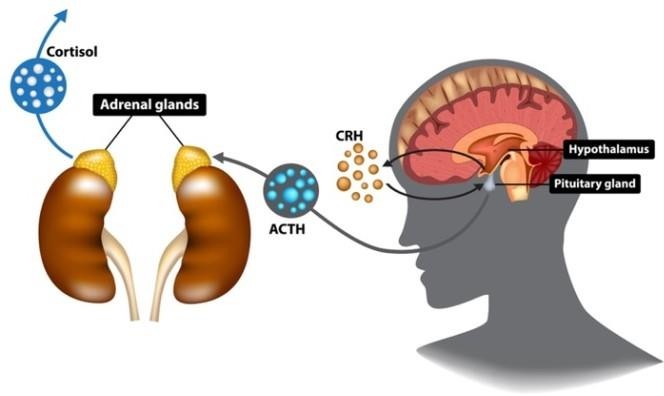
In the previous chapter, the role of the ANS, which consists of the sympathetic and parasympathetic systems in response to stress, and the role of the hypothalamus as a regulatory (or as a control center) system of the ANS were discussed. The hypothalamus is also “communicating” with the pituitary gland and adrenal cortex via hormones (Fig. 6). The organs and interactions among these three components are known as the hypothalamic-pituitary-adrenal (HPA) axis. Therefore, the HPA axis is a major neuroendocrine system that interacts with the nervous and endocrine systems, controls stress responses [82], and maintains physiological homeostasis [83].

Electrochemical sensors detect the chemical, physical, or biological parameters [84], [85] of a part of the human body (including body fluids, epidermis, specific body areas, and places). They can detect hormones, enzymes, and proteins produced by the HPA axis. Recently, such sensors have been developed in a wearable form [86]–[90]. Wearable devices are gaining increasing attention for monitoring physicochemical parameters (e.g., HR, EDA, motion, respiration rate, and skin temperature), and a combination of

biomarker monitoring is required at the next level of a more complete and sophisticated overview of health and body functioning [89]. Many of these biomarkers are involved in stress detection, monitoring, and evaluation.

Measurements are mainly performed on saliva [88], [91], [92], and eccrine sweat [92]–[94], and less on other secretions. Both (Saliva and sweat) are attractive alternatives for blood analyses. Some elements found in saliva and eccrine sweat were correlated with those found in blood.

These biomarkers are cortisol (hormone), glucose, prolactin (protein), and alpha-amylase (enzyme), which are usually detected, compared, analyzed, and related to stress. Stress-related biomarkers have been described in detail in this section.



**FIGURE 6. Stress response: The hypothalamus releases corticotropin hormone (CRH) and triggers the release of adrenocorticotropic hormone (ACTH) from the anterior pituitary into the circulation. Finally, the adrenal cortex releases stress hormones (such as cortisol) [95].**

Human physiological fluids that can be measured using noninvasive Electrochemical Biosensors include saliva, sweat (eccrine sweat and apocrine sweat), tears, interstitial fluid (ISF), and urine [87], [89], [90], [96]–[98].

1. SWEAT

Sweat is a salty fluid consisting mainly of water secreted from the skin-sweating glands of mammals. Eccrine and apocrine sweat glands are also observed. Eccrine sweat glands are present throughout the body and play a thermoregulatory role (through the evaporation effect of sweat). Apocrine sweat mainly exists in the hair follicles in the groin and axillary areas. Apocrine sweat is (more) osmotic, and apocrine sweat glands produce thicker sweat with a lower percentage of water than eccrine sweat [99], [100].

The following biomarkers [101], [102] can be identified: lactate [103], ammonia, calcium, glucose [94], [104], sodium, chlorine, potassium, ethanol, urea, cortisol [105]– [107], and various cytokines and neuropeptides.

The proper method of sweat sample collection, with an emphasis on preventing the sampling of mixed fluids and elements from other sources on the skin surface, can accurately reflect glucose [108] and cortisol [109] levels in

correlation with saliva and blood. Cortisol and glucose levels in response to stress.

Several sensors that can measure all aforementioned elements are available [87], [102], [110]–[112]. Many of these are wearable [113]–[117], whereas some are wireless [90], [107]. All these sensors have been developed and are continuously being developed, are researched and commercially available mainly for athletic and medical interests, and focus on sweat measurements [118], [119].

Skin is the largest human organ and has the largest surface area throughout the body. It provides continuous real-time detection, measurement, and quantification of biomarkers using wearable sensors, making it much more practical, convenient, and less annoying than other bodily fluids (e.g., saliva, urine, and tears).

1. TEAR

Tears are salty liquid fluid that is secreted from the tear glands (lacrimal glands) and found in the eyes. They contain water, electrolytes (which is why they are saline), proteins, lipids, and other elements. The tear film consists of three layers. From the lipid, aqueous, and mucous layers [120]. The main role of tears is to lubricate the eye, remove irritants (reflex tears), and provide immune support [121]. Pain and emotions can “bring” tears in the eyes [122].

Tear fluid sampling and analysis can be helpful in the diagnosis of eye diseases [123]–[125] and diseases other than ophthalmology [126]. Research and analysis of tears is a promising and interesting opportunity for the diagnosis of neurological diseases [127], such as multiple sclerosis [128], [129], Alzheimer’s dementia [130], and Parkinson’s disease [131], [132]. Biomarkers such as stress hormones have also been studied for stress detection and measurement [133]. In tears, the glucocorticoid hormone cortisol, glucose [134], and many other proteins [135], such as lysozyme, lactoferrin, secretory immunoglobulin A, serum albumin, lipocalin, and lipophilin.

Wearable devices (e.g., lenses) have been developed and applied for the detection of biomarkers in tears, with emphasis on stress measurements such as cortisol [136], [137], lysozyme [138], and glucose [139]–[141] (mainly for diabetic purposes). There is a correlation between glucose and cortisol levels and the stress response (cortisol increases sugars (glucose) in the bloodstream [142]).

1. SALIVA

Saliva is an attractive fluid after blood serum for detecting stress via biomarkers and the autonomic nervous system. Sympathetic stimulation can differentiate salivary flow. Some biomarkers detected in saliva include alpha-amylase, uric acid (UA), glucose, lactate, phosphate, cortisol, and lysozyme [143]. Diurnal and seasonal variations in hormones such as cortisol (normally higher in the morning and lower at night) must be considered [144], [145].

Research, detection, and measurement of salivary biomarkers [146]–[148], especially α-amylase [149]–[153],

cortisol [154]–[156], lysozyme [157], prolactin [158], [159], and glucose [160]–[162] have been conducted.

α-Amylase, which is secreted by the salivary glands, is an ideal biomarker for stress detection in saliva because it is controlled by the autonomic nervous system. The response of amylase to stress is fast and immediate, unlike cortisol, which takes time (minutes later) [163].



**FIGURE 7. Digital sensors provide information on activity and location, together with emotional data, with the purpose of creating a background picture of health (salivary in-mouth sensors) [164].**

Biochemical sensors [165]–[167] are sometimes wearable [87], [91], [92], [97], [168] and can measure (or are almost there) most of these biomarkers, especially α-amylase and cortisol, which are the so-called stress hormones”.

Wearable sensors in the mouth (saliva) are impractical to use and difficult to wear, as they are in other areas of the body (e.g., sweat on the skin). Therefore, continuous real- time stress detection is cumbersome.

1. URINE

Urine is a metabolic fluid found in humans and animals. Kidneys clean the blood from toxins and other elements that must be removed and transformed into urine. Urine flows to the ureters and then to the urinary bladder; finally, it is discarded through the urethra [169].

Urine is an attractive fluid for the prognosis and diagnosis of certain diseases [170]–[176]. Thus, urine is usually tested for (a) biomarkers that are not normally present due to illness or injury and (b) the detection of normal biomarkers that are increased or decreased, including urinary incontinence, glucose measurement (for diabetic patients), and oxidative stress biomarker measurement [177] as a chronic disease, rather than (an acute) stress response, which is not very convenient.

Glucose is an attractive biomarker for stress detection and measurement in the urine using wearable sensors. To accomplish this, wearable devices designed and developed for people with diabetes have already been developed [178]. Urine and blood glucose levels are potentially correlated [179].

1. INTERSTITIAL FLUID (ISF)

Interstitial fluid (ISF) surrounds cells in the body, constituting 15–25% of body weight [180]. It is comparable to blood plasma and functions on one hand as a fuel station that provides nutrition to cells and on the other hand, as a waste product removal mechanism from the cells [181].

ISF is considered unexplored for biomarker detection and measurement [182]. Therapeutic and opioid (drug) monitoring using the ISF biomarker detection [183]–[187] is promising. ISF is certainly advancing in wearable glucose measurements, particularly in patients with diabetes (usually type I diabetes) [188]–[190]. Glucose and cortisol are probable biomarkers of ISF that are related to stress responses and can be measured.

ISF is primarily accessed and sampled using microneedles [191]–[195] and iontophoretic extraction [196]–[198]. Both procedures were minimally invasive [199]. Wearable devices are available to detect and measure glucose and cortisol levels in response to stress stimuli [188]–[190], [200], [201]. The combination of biomarker detection and measurement from sweat and ISF with one sensor or one device platform is another interesting idea and is probably a promising opportunity for biomarker measurements because both sweat and ISF sampling devices are located on the skin [202].

ISF access and sampling is a minimally invasive method compared with noninvasive methods, which is a serious disadvantage that prohibits market acceptability.

* 1. ***BODY MOVEMENTS***

The use of new-generation three-dimensional (3D) accelerometers and fitted gyroscopes, for example, on a smartwatch, is an important tool that can be used to evaluate stress.

The motion must be evaluated during the stress measurements. However, different analytical methods are required in certain situations. For example, social stress differs from the stress induced by running, walking, or rowing. Wearable devices such as accelerometers and gyroscopes can generally detect body activity movements and sometimes the exact activity that occurs. Thus, these data can be co-evaluated for the final outcome.

Stress, particularly social stress, can also induce tremors. Usually, stress increases the heart rate, blood pressure, and breathing rate, and muscles are likely to be more tensed. This could induce shaking and tremors.

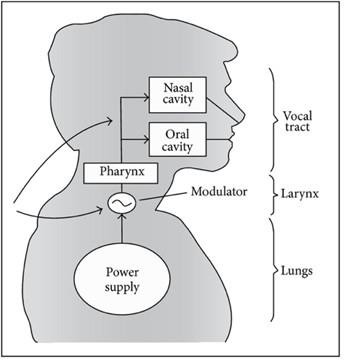
A ballistocardiogram (BCG) measures the ballistic forces generated by the heart (during systole), and is useful for measuring the pulse transit time (PTT), heart pulse rate, and pulse wave analysis fusion (PWA) to assess arterial stiffness. Theoretically, (cuffless) blood pressure can be obtained. A microelectromechanical system (MEMS) tri-axial accelerometer is used for this measurement, usually at the wrist, ear, and other body positions.

* 1. ***SPEECH***

Speaking is quite complex; it goes through several stages until the voice gets out in a meaningful manner. Many human organs are involved in this procedure, such as the lungs, pharynx-vocal cords, oral and nasal cavities, and brain [203]. Speech exhibits certain characteristics. Has a tone, it has a flow, it has a volume, it is sometimes melodically or in a

strict tone, it is shadily or happily, it is lively or tired? Researchers have found that reading and speaking (especially aloud) involves activating the autonomic nervous system (by requiring respiration) [204], [205].

All the above-mentioned (organs and body parts) must be functional, in good health, well-coordinated, especially by the brain, and work in harmony. Thus, the induced stress may cause significant changes in speech [206]–[208].



**FIGURE 8. Speech production method (from the lungs and vocal folds to the nasal and oral cavities) [209].**

* 1. ***BODY POSTURE***

Posture is considered to be affected by stress. Changes in posture, along with other signs (such as breathing rate) can be assessed as a result of stress [210]. However, the opposite effect was observed. That is, wrong – poor posture to induce more stress (among other things such as adversely affect pulmonary function [211], adverse musculoskeletal conditions, etc.) and posture correction to decrease stress on individuals [212].

Various wearable devices are available for studying and evaluating posture (body and head) [213], [214]. Smart clothes [215]–[219], vests [220], [221], patches [222], and watches (wrist) [223]. Some technologies and sensors used for posture measurement evaluation include motion sensors [224], accelerometers [225], strain gauges [226], flexible –

piezoelectric sensors [227], [228], fiber-optic goniometers

[229], inductive sensors [230], ergonomic dosimeters [231], and inertial sensors [232].

* 1. ***HAND TREMOR***

A shaking hand may be a stress indicator, among many others of course. Some of the causes that may induce or increase the symptoms of hand tremors include Parkinson’s disease, alcohol withdrawal, multiple sclerosis, stress- anxiety, fatigue, and high caffeine consumption [233]–[235]. Hypoglycemia may also be involved in hand tremors, and wearable devices that can detect hand tremors (as a warning)

for this life-threatening condition have been developed [236]. Furthermore, Parkinson’s can be evaluated using hand tremors [237], [238].

Thus, existing devices for measuring hand tremors for other purposes, even for common health monitoring (e.g., smartwatches) with accelerometers, gyroscopes, adequate computing resources, internet connectivity via Wi-Fi, Bluetooth, 4G, or 5G, and the use of artificial intelligence (AI) can measure hand tremors [239] and can also be co- evaluated with other biosignals and/or biomarkers for stress detection – measurement.

## STRESS DETECTION TECHNOLOGIES

* 1. ***OPTICAL***

Light, either in the visible or infrared spectrum, was used for biomarker measurements.

* + 1. PHOTOPLETHYSMOGRAPHY (PPG)

PPG is a noninvasive technology in which light is emitted from low-consumption and high-efficiency LEDs to measure the heart rate, frequency, and other parameters through reflection or light absorption [240]–[242]. When a heartbeat occurs, blood flow increases and differentiates the reflection or absorption of light. Using digital signal processing filtering methods (to reduce noise and motion artifacts), the blood volume pulse (BVP) can be obtained [243]–[245].

Heart rate (HR), heart rate variability (HRV), and respiratory rate can be measured with high accuracy by measuring the frequency or period of pulses per unit time [246]–[248]. In addition, blood oxygen saturation (SpO2) can be measured using PPG [249]. BP is also expected that BP will be continuously measured via PPG [250]–[253] using various methods and signal combinations (bio- impedance, pulse wave transit time (PWTT), AI, etc.) with relatively good measurement accuracy or even medical precision [254].

* + 1. INFRARED (IR), NEAR IR (NIR) SPECTROSCOPY (NIRS), AND FUNCTIONAL NIR SPECTROSCOPY

Infrared (IR) light is electromagnetic radiation (EMR), which is similar to human visible light. The wavelength of human visible light ranges from 400 nm to 700 nm [255]. Thus, IR was greater than 700 nm (between 780 nm and 1 mm). Near- infrared (NIR) light is called infrared light, next to human visible light, and there are also the terms mid- and far- infrared light. The NIR wavelength ranges from 0.78 μm to 3 μm (or 780 nm to 3000 nm) [256].

Pulse oximetry is a noninvasive, portable, and wearable method that uses infrared light, usually in thin parts of the human body (such as the fingertip, earlobe, and wrist), to measure oxygen concentration or oxygen saturation. A red LED (wavelength of approximately 650 nm) and an infrared (NIR) LED (wavelength of approximately 950 nm) were used. Blood saturated with oxygen absorbs more infrared light and allows more red light, and vice versa (when it is low oxygen-saturated). Therefore, blood-oxygen saturation is

measured by absorption or non-absorption of red and NIR light [257]–[259].

Infrared thermography (IRT) and infrared thermometry (IRTM) are noncontact, portable, and wearable IR temperature measurement methods. Every object emits more infrared (IR) light when heated. IR lenses and thermopile sensors [260] are typically used to sense heat (via IR light). Using this method, the skin temperatures of humans and animals can be measured [261]. The measurement distance is also a factor, and all devices have limitations.

Near-infrared spectroscopy (NIRS) is a non-invasive method that employs near-infrared light (first used in biomedicine to examine the optical characteristics of hemoglobin) to measure arterial blood oxygen saturation and hemodynamics in general. It was later implemented and applied to the human scalp by analyzing the reflection of transmitted–emitted NIR light to human tissue [262].

Functional infrared spectroscopy (fNIRS) is a portable, wearable NIRS technique for the functional monitoring and imaging of human brain hemodynamics. This method is used to monitor and evaluate several problems and conditions at the brain level, including epilepsy, cognitive dysfunction, and anxiety [250]–[252]. In addition to other methods, such as fMRI, electroencephalography (EEG) can provide a fuller and more comprehensive view of a human’s brain situation [266].

* + 1. VISUAL OBSERVATION - IMAGING

Visual observation can reveal human health conditions and possible health problems. Cases such as iris of the eye, eyelid opening and closing lapses, skin discoloration, or facial cues can be detected using a camera (with the assistance of appropriate software) [254]–[257].

Wearable devices, such as helmets equipped with a CCD or CMOS camera sensor, along with facial image tracking, recognition, object detection mechanisms, and data analysis, which are usually implemented using AI machine learning (ML) systems [271]–[273], are possible.

Imaging techniques include thermal imaging (TI), hyperspectral imaging (HSI), and broadband imaging. Almost all of these have already been used by researchers for emotional–cognitive stress detection [274]–[278].

* 1. ***ELECTRICAL***

In the human body, organs such as the heart or brain produce electrical signals that often reveal the state in terms of health, activity, emotions, and stress at the time of measurement or for some time if the measurement has some duration. Some measurements that can be made using wearable devices are as follows:

* + 1. ELECTROENCEPHALOGRAPHY (EEG)

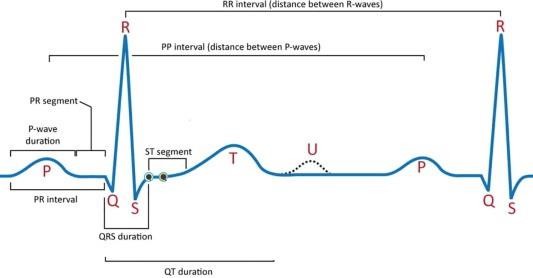
It is a graphical recording of the electrical activity of the surface layer of the brain from the scalp [279]. Among other methods, EEG is usually used for the diagnosis of certain illnesses or conditions, such as epilepsy, anesthesia, sleeping disorders, encephalopathies, coma, dementia, trauma, and death (brain death).

EEG records the following rhythms Alpha (8 Hz to 13 Hz), Beta (13 Hz to 30 Hz), Gamma (30 Hz to 100 Hz), Delta (0 Hz to 4 Hz), and Theta (4 Hz to 8 Hz), at various locations of the head [280]. For example, beta waves are located in the frontal and parietal regions and respond in a state of alertness, active thinking, panic attack, and concentration as well as neurotransmitters and hormones related to adrenaline, cortisol, and dopamine, which are active or related to stress responses to stress stimuli.

Therefore, the EEG method, alone or in combination with other methods (such as HRV and EDA), has been used in research and many scientific articles have been published on the detection and quantification of stress responses [55], [281]–[286]. Recently, the idea of using wearable EEG devices have become increasingly attractive for the detection of stress responses in real life, working environments (particularly trucks and buses), and mental health management [51], [287]–[294]. Commercially available wearable EEG devices are available [295]–[297].

* + 1. ELECTROCARDIOGRAPHY (ECG)

It is a graphical representation (voltage/time) of the electrical activity of the heart. A normal ECG has a unique characteristics (marks, curves, peaks, etc.) that have a specific serial–temporal sequence and duration within certain time limits [298].



**FIGURE 9. Typical ECG graphical representation with all associated valuable information [299].**

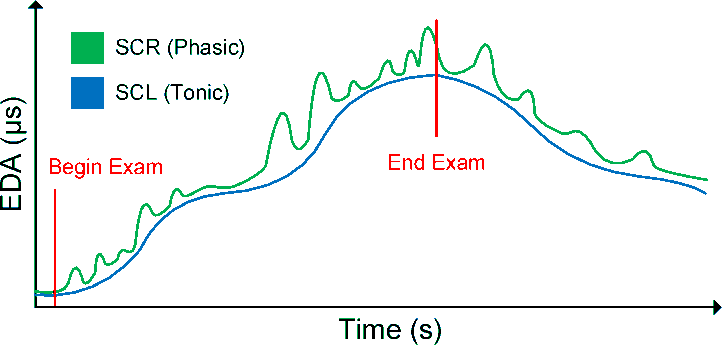
The interpretation of an electrocardiogram and its possible exclusions from a normal electrocardiogram can assist physicians in diagnosing certain diseases (such as atrial fibrillation, atrial flutter, arrhythmias, tachycardia, and bradycardia) and drawing conclusions on someone’s health condition [300]. Measurements, such as heart rate (HR) and heart rate variability (HRV or R-R Interval), can be extracted relatively easily from an ECG, even from non-medically educated personnel. Both HR and HRV have been associated with stress detection and measurement in many studies [301], [31].

Wearable devices, such as watches, have ECG capabilities, whereas others appear to have medical accuracy [302],[303].

* + 1. SKIN CONDUCTANCE RESPONSE (SCR) –

GALVANIC SKIN RESPONSE (GSR)

Occasionally, the skin becomes an adequate electrical conductor. This usually occurs when there is psychological or physiological arousal. This is typically measured by using two electrodes. A small electrical charge was applied between the two endpoints of the electrodes on the skin. Skin conductivity was observed, monitored, and/or recorded (in microsiemens (µS)). The conductance level typically varies, and the manner in which it varies provides valuable conclusions [304],[305],[306].



**FIGURE 10. Electrodermal Activity (EDA). Baseline conductance or (tonic) skin conductance level (SCL) and (phasic) skin conductance response (SCR) [307].**

To obtain valuable information on stress detection, analysis of the conductance signal level is required. The skin conductance baseline in a graphical representation of the individual person and the measurement must be delineated because of the variations. The baseline response curve is smooth, and any sharp (rapid/sudden) bend in this curve indicates autonomic nervous system arousal after an external or internal stimulus [308],[309].

To detect and evaluate stress, it is necessary to distinguish between the baseline (tonic) conductance and phasic conductance, which may be the result of a stressor, as shown in Fig. 10. SCR is typically combined with other methods (e.g., EEG and ECG) for stress assessment [310]– [312].

* + 1. ELECTROMYOGRAPHY (EMG)

EMG is used for the diagnosis and detection of abnormalities in the muscles, neurons, or both. Electrical signals obtained using electrodes from neuronal and muscle activities have been collected, analyzed, and evaluated [313],[314]. The trapezius muscles have been considered as stress predictors in some studies [315],[316]. The sole EMG method, or more frequently complementary to other methods, such as EEG, ECG, and HRV, is used in some cases to detect stress response and activity [317]–[319].

* + 1. BIO-IMPEDANCE

Bioimpedance refers to the response of living organisms to an externally applied electric current. The body impedes the electric current flow. For instance, the blood impedance is lower, whereas the fat impedance is higher. Therefore, bioimpedance is used for body composition and blood flow analysis [320], [321].

With electrical impedance plethysmography (EIS) and other techniques, the volume of a cardiac blood pulse can

be measured along with the pulse wave velocity (PWV), pulse transit time (PTT), or pulse wave transit time (PWTT) [321]–[323]. Knowing all the above measurements, cuffless blood pressure estimation is also possible [324], [325].

Wearable patches and watches [326]–[328] use electrical bioimpedance to measure cardiac output, stroke volume, and blood pressure. Bioimpedance and other measurements of the human body can assist in indirect measurement and evaluation of stress.

* 1. ***ELECTROMECHANICAL***

Electromechanical sensors are related to mechanical energy and response – stimulus – motion, which is converted to an electrical signal at an analogous rate, usually measured in volts. For example, slow motion, low voltage, and fast motion result in a high voltage [329].

Some mechanical applications in which electromechanical sensors are applied to the human body in a wearable form include stress gauges, strain, motion- inertial, and pressure sensors. They can be used for dynamic monitoring of human posture [330], tremors, pulses, oscillations, vibrations, and other physiological and motion parameters [331]–[336]. They are used by athletes and patients and generally for health monitoring purposes.

Inertia electromechanical sensors [337] are flourishing nowadays and are embedded in smartwatches and smartphones in the form of accelerometers and gyroscopes for motion detection, such as positioning, steps, sleeping monitoring, athletic activities, wellness, and healthcare in general [338]. It is interesting to use these sensors for several reasons:

Ballistocardiogram (BCG): measurement of ballistic forces generated by the heart (during systole) acting on the entire body [339].

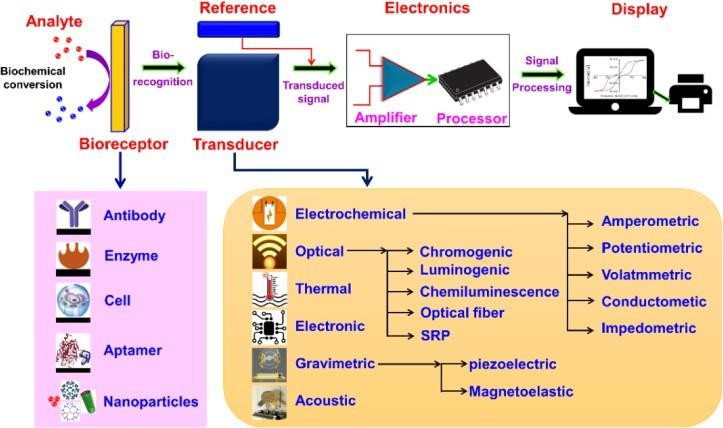
Seismocardiogram (SCG): Measurement of mechanical vibrations induced by the heart locally on the chest ( not for forces acting on the entire body, such as BCG) [340]–[342]. BCG and SCG are useful for measuring pulse transit time (PTT) and heart pulse rate. With pulse wave analysis fusion (PWA) to assess arterial stiffness) and with other complementary measurements, theoretically, a (cuffless) blood pressure can be obtained [343], [344], [345]. Wearable MEMS triaxial accelerometers and gyroscopes are used for these measurements, typically in the chest,

wrists, ears, and other body areas.

* 1. ***BIOCHEMICAL - ELECTROCHEMICAL***

Biochemical biomarkers are another way to identify, detect, and measure metabolites (such as saliva and sweat), volatile organic compounds (VOCs), ions, and hormones (stress and anti-stress hormones) related to stress [346]–[349].

A biochemical-electrochemical sensor can convert a chemical (or biological) reaction response to an electrical signal, providing the potential for personalized continuous monitoring and treatment related to stress [350].



**FIGURE 11. Schematic representation and components of typical (electrochemical) biosensors [351].**

Wearable noninvasive (or semi-invasive) biochemical sensors can be used to apply/measure parameters from the epidermis (sweat), intestinal fluid, tears, saliva, and urine. [350], [352], [353]. Data signals are transmitted wirelessly using RFID, Bluetooth, and other wireless access technologies for the monitoring devices.

* 1. ***BIO-KINETIC***

Another recently investigated method for stress detection is movement analysis using accelerometers and gyroscopes. The movement of the hands (e.g., trembling), typing on a computer (change in rhythm, pattern of typing), and (nervous) movement of the body in general can reveal the existence of stress.

Table 1 presents some of the most commonly used wearable devices for stress-response measurements.

## SENSOR DATA NETWORKING

* 1. ***DATA FORM***

In general, we can categorize the data from the various stress-detection wearable devices into two categories, which are the following:

* + 1. RAW DATA

Raw or primary data are the original data that have not been processed or modified. The raw data are altered so that they can be useful for a process. Wearable devices with sensors store, transfer, and produce processed data even in real-time (e.g., processing and transferring ECG or PPG signal data).

* + 1. SHAPED DATA

It is data that has undergone some kind of processing, merging, or juxtaposition (e.g., in tables and datasets) with the aim of making the data easier to read–to compare, more meaningful, and semantic. Furthermore, the data can be graphically illustrated and statistically processed.

* 1. ***DATA TRANSFER***

Data transfer and signal technologies from wearable devices and sensors can be divided into two categories: wireless and wired technologies.

* + 1. WIRELESS

In recent years, wireless data signal transfer has rapidly developed and implemented. Various wireless transmission methods and technologies were selected and applied according to the requirements of each application. The following are typically used:

* + - 1. Wi-Fi

Wi-Fi is a standardized data transfer protocol used in almost every home. It has a small and medium coverage range, which is usually larger than that of Bluetooth, offers excellent networking, and provides powerful data security.

* + - 1. BLUETOOTH

Bluetooth is a standardized data transfer protocol that is widely used and provides a relatively small-to-medium coverage range.

* + - 1. ANT+

ANT + is a short-distance data-transfer protocol similar to Bluetooth, and its data-transfer volume is relatively small.

* + - 1. CELLULAR TECHNOLOGY

Cellular technologies (2G, 3G, 4G, and 5G) are well-known mobile interconnections and communication network technologies. If a wearable device has the necessary equipment and a SIM card, it can connect and transfer data through this network, thereby providing a wide coverage range. 5G networking technology provides better connectivity than previous generation cellular network technologies, a faster response, lower latency, and higher data flow. However, it has a few limitations (it is available mainly in urban areas with a high intensity and frequency of 24GHz and above).

* + - 1. NFC and RFID

Near-field communication (NFC) and radio frequency identification (RFID) are sets of protocols for establishing one- or two-way communication between electronic devices at distances of 5 cm or less for NFC and a maximum of 25 m to 100 m (using batteries) for RFID.

* + 1. WIRED

Wireline data transfer offers no new or innovative solutions in the research field. They have existed for many years with some improvements over time. The volume of data from biometric sensors of this type is usually not large and the transfer speed is not very demanding. Universal Serial Bus (USB) cables and various types of electrodes were used.

Electrodes (and common cables) are electric conductors that can carry electric signals from non-metallic surfaces, such as solids (human skin, liquids, vacuum, gases, etc.). Amorphous carbon, gold, and platinum are some of the materials that can be used in electrodes. Common electric cables can transfer raw signals from electrodes to a wearable stress-detection device, which can then store, analyze, transform (to shaped data), and display data.

The following table (TABLE 1) presents a list of available devices – sensors that use almost all the methods and technologies mentioned in this document-at various locations on the human body. These devices are available for commercial, medical, academic, and research purposes. Alone or in combination, they can or may be used exclusively or partially to monitor stress.

TABLE I

WEARABLE DEVICES USED FOR STRESS DETECTION PURPOSES

Device Description Body location Measurements Type of use

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| AutoSense [354] | AutoSense is a wearable wireless sensor system for continuous assessment of personal exposures to addictive substances and psychosocial stress | Chestband | 2-leadECG, GSR,  respiratory inductive plethysmograph (RIP) band for measurement of respiration, skin temperature, ambient temperature, and a 3- axis accelerometer | Research, academic |
| Biobeat (watch & patch) [355] | Continuous  monitoring of vital signs | Wrist (watch), chest (patch) | HR, HRV, skin temperature, blood pressure, ECG (patch only), cardiac index - output etc. | Medical |
| Caretaker Medical + ETCO2 Sensor [356] | Wireless patient monitoring platform adds | Finger-cuff + wrist | Carbon dioxide monitoring, blood pressure, heart rate, and respiration rate | Medical |
| Dexcom G6 & G7 [357] | Continuous glucose monitoring (CGM) system | On the back of the upper arm/abdomen, or upper buttocks | glucose monitoring | Medical |
| E4 Empatica –  EmbracePlus [358] | Smartwatch for continuous health monitoring | Wrist (watch) | EDA, HR - HRV - IBI,  skin temperature, accelerometer and  gyroscope. | Medical (only EmbracePlus), reasearch |
| EMOTIV EPOC X,  Insight, MN8 headsets [359] | Contextual human brain research | Head - headset | 14-CHANNEL EEG  whole-brain sensing, 5- CHANNEL & 2-channel | Research, personal |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | EEG |  |
| Fitbit Sense 2 [360] | A stress, wellness, and sleep management watch | Wrist | SpO2 (blood oxygen) tracking , heart rate tracking, EDA scan, heart rate variability, skin temperature sensor, breathing rate. | Commercial |
| Flowtime [361] | Biosensing meditation headband with heart rate and brainwave sensors | Headband | 2-channel brainwave and heart rate (HRV) sensors | Commercial |
| GlucoMen areo 2K [362] | Remotely monitor the glycemic trend and share data with your medical staff and caregivers | Wrist (watch) | Glucose Oxidase (Glycaemia), ketonemia | Medical |
| GraphWear [363] | Wearable glucose monitor with no needle | Wrist, abnomen (patch) | Glucose measurement | Reasearch |
| HealthPatch MD [364] | Cardiac sensor worn as a patch | Chest patch | ECG, heart rate and heart rate variability, respiratory rate, skin temperature, body posture and fall detection | Medical |
| Heart2Save’s Awario [365] | Arrhythmia detection | Jewellery (two fingers touch) | 1-channel ECG data | Medical |
| Hipee Xiaomi [366] | Smart posture trainer & corrector | Neck - shoulder | Tracking and analyzing posture in real-time | Commercial, personal |
| Imec ECG necklace [367] | Wearable ECG and physical activity monitor | Neck, chest | ECG holter monitoring, HRV (heart rate variability) measurements. | Clinical |
| Interaxon Muse 2 & S [368] | Meditation & sleep support | Headband | EEG, PPG - pulse oximetry (heart rate), accelerometer, gyroscope | Commercial |
| K' Watch [369] | Bloodfree continuous glucose monitor (CGM) smartwatch | Wrist (watch) | Glucose | Under developement |
| Lab-on-Skin™ Technology xsensio [370] | Biochemistry and microfluidics Lab-on- SkinTM sensing chip (5x5mm) to continuously collect ISF at the surface of skin, proprietary sensing platform with variety of sensors. | Arm (patch) | With customization of the chip and sensor: cortisol, pH level and Na+ and  K+ concentrations etc. | Reasearch |
| Microsoft Band 2 [371] | Health and fitness device | Wristband | Optical heart rate sensor, 3-axis accelerometer, gyrometer, skin temperature sensor, UV sensor, capacitive sensor, galvanic skin response | Commercial |
| Mindfield eSense Skin Response [372] | Device for stress indication and  meditation | Hand fingers | Skin conductance | Commercial |
| MindWave mobile EEG headset [373] | Monitors the level of attention and relaxation | Headband | EEG | Commercial |
| Movesense [374] | Wireless wearable sensor for patient and sports monitoring needs | Chestband | ECG, HR, HRV (heart rate variability) and motion measurement | Medical |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| NIRSport2 [375] | Wearable - wireless functional near-infrared spectroscopy (fNIRS) platform which measures hemodynamic responses | Head (headgear) | fNIRS,Probe-level 9- axis accelerometer(s) | Research |
| O2Ring [376] | Continuous oxygen monitor | Hand finger | Tracking continuous oxygen level and heart rate | Commercial |
| Oura ring [377] | Wearable (ring) with variety of measurements for wellness, activity and stress monitoring | Hand finger | Heart rate, HRV, SPO2, skin temperature, 3D accelerometer | Commercial, research |
| Prana [378] | Tracker for breathing and posture | Weist | Breathing, posture | Commercial |
| Sentio Solutions Feel Therapeutics [379] | Continuously monitor a variety of physiological signals to extract metrics and insights related to the mental health | Wristband | HR, HRV, EDA,  physical activity, skin temperature | Commercial |
| Shimmer3 ECG, Shimmer3 EMG, Shimmer3 GSR+ and more [380] | Wearable sensor products for biophysical and kinematic data capture | Wrist, chest, leng, fingers | ECG, EMG\*, PPG,  GSR, respiration, 9 DoF inertial sensing | Commercial |
| Shimmer sensors, Verisense | One wearable sensing platform | Wrist, fingers, arm | Accelerometer, gyroscope, PPG and GSR signals | Clinical, research |
| Stanford  University, wearable device [116] | Wearable device which measures cortisol in sweat | Arm - wrist (patch) | Cortisol (stress hormone) | Research, academic |
| The HandWave Bluetooth Skin Conductance Sensor [381] | HandWave is a wireless skin conductance sensor to detect information related to emotional, cognitive, and physical arousal of mobile users | Hand (handglove) | Skin conductance | Research, academic |
| UCLA Smartwatch [119] | Developed at UCLA measures cortisol hormone in sweat | Wrist (watch - patch) | Cortisol (stress hormone) | Research, academic |
| Zephyr sensors [382] | Optimized training and practice habits.  Improved physicality and energy | Body, straps and shirts | ECG - HR - HRV,  respiration, estimated  core body temperature, accelerometry | Academic, research, sports |

1. **DATA ANALYSIS METHODS**

A major scientific trend concerning the analysis of data collected from wearable systems to detect and evaluate stress involves Artificial Intelligence (AI) and, more specifically, Machine Learning (ML) and Deep Learning (DL) (both subsets of AI). During the last decade, AI has mainly been used for data analysis and evaluation of all collected data in such a manner that the presence of stress can be predicted and managed accordingly.

* 1. ***ARTIFICIAL INTELLIGENCE (AI)***

AI is a major chapter in information technology and has many subsets such as ML and DL. Also, Fuzzy Logic (FL) is applied to AI (as a form of AI).

ML is the most frequently used mechanism for stress data analysis [383]–[390], which continuously improves the

outcome (evaluation), as long as more data are collected. The main ML methods that exist are as follows:

* supervised learning (regression, classification)
* unsupervised learning (clustering)
* reinforcement learning (q-learning)

DL [390]–[392] imitates the human brain to learn and uses a large amount of data (usually more than a common ML system). Neural Networks (NN) form the backbone of DL systems.

Some ML algorithms used for the data analysis of a stress-detection system are as follows:

* Random Forest [393]–[396]
* Support Vector Machine (SVM) [397]–[401]
* k-Nearest Neighbors (kNN) [402]–[404]
* Fuzzy Logic [405]–[408]
* Decision Trees [409], [410]
* Principal Component Analysis (PCA) [411]– [413]
* Artificial Neural Network (ANN) [414]–[416]
* Ensemble Methods [417], [418]
* Naïve Bayes [419], [420]
* Linear Discriminant Analysis [421]–[423]
  1. ***STATISTICAL ANALYSIS (SA) AND DATA MINING (DM)***

SA and DM are important tools in modern ML [424]. Statistics are used in the data analysis of a stress-detection mechanism, particularly at the pre-analysis level or as an additional support tool to extract meaningful relationships between the data.

The following table (TABLE II) presents modalities – combined methods, along with models of artificial intelligence (AI) algorithms and data classifications used in various studies, and the accuracy achieved in each case from 2010 onwards (Arsalan et al. 2022 [425]).

TABLE 2

Summary of Multimodal Human Stress Detection Studies (with and without wearables) [425].

Method Type of Stress Modalities Classifier Accuracy

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| (Al-Shargie et al., 2016) | Acute | EEG, fNIRS | SVM | 95.10% |
| (Kyriakou et al., 2019) | Acute | GSR, ST | - | 84.00% |
| (Can et al., 2019b) | Acute | HR, GSR, Acc | MLP | 92.15% |
| (Lee et al., 2016) | Acute | Acc, Gyro, Mag | SVM | 95.00% |
| (Chen et al., 2017) | Acute | ECG, GSR, RR | SVM | 99.00% |
| (Ghaderi et al., 2015) | Acute | RR, GSR, HR, EMG | SVM, kNN | 98.00% |
| (Gjoreski et al., 2016) | Acute | BVP, HR, ST, GSR and RR | RF | 92.00% |
| (Sano and Picard, 2013) | Acute | SC, Acc | SVM, kNN | 75.00% |
| (Hovsepian et al., 2015) | Chronic | RR, ECG, Acc | SVM | 95.30% |
| (Zubair et al., 2015) | Acute | EDA, Acc, Bluetooth | LR | 91.00% |
| (de Santos Sierra et al., 2010) | Acute | HR, EDA | kNN | 95.00% |
| (Sandulescu et al., 2015) | Acute | PPG, EDA | SVM | 80.00% |
| (Mozos et al., 2017) | Acute | EDA, PPG Acc, microphone | kNN, SVM, AdaBoost | 94.00% |
| (Kurniawan et al., 2013) | Acute | GSR, Speech | k-mean, SVM, GMM | 92.00% |
| (Aigrain et al., 2016) | Acute | EMG, GSR RR, Kinect | SVM | 85.00% |
| (Baltaci and Gokcay, 2016) | Acute | pupil dilation, periorbital temper. | ABRF | 65%-84% |
| (Huang et al., 2016) | Acute | Eye gaze, mouse click behaviour | RF | 60.00% |
| (Akhonda et al., 2014) | Acute | EEG, ECG, EMG, EOG | NN | 80.00% |
| (Ahn et al., 2019) | Acute | EEG, ECG | SVM | 87.50% |
| (Muaremi et al., 2014) | Acute | ECG, GSR, ST, RR | SVM, kNN, NN, RF, LR | 73.00% |
| (Xu et al., 2014) | Chronic | EEG, ECG, GSR, EMG | k-Mean | 85.20% |
| (Sriramprakash et al., 2017) | Chronic | ECG, GSR | SVM, kNN | 72.82% |
| (Hosseini and Khalilzadeh, 2010) | Acute | GSR, EEG, BVP | SVM | 84.10% |
| (Wijsman et al., 2013) | Acute | HR, HRV, GSR, EMG, RR | GEE | 74.50% |
| (Rigas et al., 2011) | Acute | ECG, GSR, RR | BN | 96.00% |
| (Wijsman et al., 2011) | Acute | ECG, RR, GSR, EMG | LBN | 80.00% |
| (Gjoreski et al., 2016) | Acute | GSR, EMG, HR, RR | RF | 92.00% |
| (Cho et al., 2019b) | Acute | PPG, Thermal imag. | NN | 78.33% |
| (Betti et al., 2017) | Acute | ECG, EDA, EEG | SVM | 86.00% |
| (Liew et al., 2015) | Acute | HRV, Cortisol | FAM | 80.00% |
| (Giakoumis et al., 2012) | Acute | ECG, GSR, Acc, Video | LDA | 100% |

## DISCUSSION

* 1. ***STRESS DETECTION MAIN METHODS AND ADDITIONAL PROPOSALS***

Looking at the present and both tables (TABLE 1 and TABLE 2, devices and methods of stress detection), we can draw some conclusions and propose solutions.

* + 1. AUTONOMIC NERVOUS SYSTEM (ANS) RESPONSE- RELATED MEASUREMENTS FOR STRESS

Electrocardiography (ECG) is the most widely used technique to acquire characteristic signals for stress measurements. Modern ECG devices can calculate and derive heart rate (HR) and heart rate variability (HRV-RR intervals). The galvanic skin response (GSR) is a signal with some useful characteristics: a quick response to stress (using the sympathetic system) and no intervention on the

skin from the parasympathetic system (sympathetic and parasympathetic are antagonistic systems). Therefore, this is a less complicated signal for stress detection. A combination of HR-HRV and GSR signals is recommended and wearable devices are available for (this) implementation.

New devices (smartwatches) that can measure dynamically, cuffless, and continuous blood pressure using bio-impedance and other methods (pulse transit time [PTT]) are promising innovative solutions for stress measurement optimization.

Brain activity measurement techniques such as electroencephalography (EEG) are regarded as impractical; however, in some cases (e.g., offices and cockpits), when a cask, helmet, or headset can be worn, they are efficient. Usually, the HR and other signals (such as HRV and temperature) can also be measured using EEG devices.

* + 1. HYPOTHALAMUS-PITUITARY-ADRENAL (HPA) AXIS RESPONSE-RELATED STRESS MEASUREMENTS

Cortisol is a well-known stress hormone. A wearable device with the ability to measure this hormone or other related (to stress) hormones, enzymes, and proteins is also an innovative, complementary, and auditable method for detecting, calibrating, and quantifying stress.

* + 1. ADDITIONAL MEASUREMENTS FOR STRESS

Well-established devices, methods, and technologies in areas other than stress are presented here for the sole, but mainly complementary, use of stress detection and stress monitoring optimization with all the appropriate adaptations. For example, wearable devices for Parkinson’s disease (hand tremor), diabetes (continuous glucose measurement), driver and pilot tracking of alertness (eye dynamics), and other devices or sensors for athletic performance monitoring have been correlated with stress- response detection and grading.

* 1. ***STRESS IDENTIFICATION, CATEGORIZATION, AND PARADIGMS***

This review can also help better understand stress-cause identification (at least on some occasions), stress categorization (positive or negative stress, exogenous or endogenous stress), and stress-mimicking (pseudo-stress) recognition. The following are some characteristic paradigms:

* + 1. A stress response was detected and a 3D accelerometer detected intense physical activity. This was probably because of physical activity, which is a positive endogenous stressor.
    2. A stress response was detected and the outside temperature changed significantly. Causes of exogenous temperature.
    3. A stress response was detected and the skin and body temperatures were high. This was probably due to fever (endogenous–negative stress).

In the above paradigms, if cortisol levels do not increase (after a few minutes), then it is not stress (pseudo-stress). Furthermore, artificial intelligence (AI) with self-learning

or guided learning methods in combination with the aforementioned methods can prove very helpful in this area. Additionally, searching for a source of stress through self- awareness may be helpful.

* 1. ***SUGGESTIONS, COMPLEXITY, COST, AND LEGAL- ETHICAL ISSUES***

Most scientific studies have focused on measuring the acute stress caused by specific stressors. Researchers established a baseline measurement (usually using reliable and trial methods) before the experiment. They then measured stress levels during the initiation of the stressor, its peak, and during the recovery period. Finally, the results were compared to estimate the precision of the trial (method).

Real-life continuous stress measurement scenarios using wearable devices are significantly more complex. A more sophisticated and multi-input data approach from (both) the ANS and HPA axis and other feedback is required. Verification of the measurements in experiments is often performed using hormone measurements such as cortisol, enzymes such as α-amylase (in blood, saliva, and sweat), and questionnaires such as the Perceived Stress Scale (PSS) and its derivatives.

Watches are the most widely used wearable device. There are smartwatches (TABLE 1) for commercial, medical, and research uses that can or are about to measure the following continuously or frequently:

1. Heart rate (HR), heart rate variability (HRV), and blood oxygen saturation (SpO2) via photoplethysmography (PPG optical sensor).
2. Ambient and skin temperature (ST) measurements using infrared (IR) sensors.
3. Movement: steps – physical activity tracking via 3-axis (3D) accelerometer (ACC) and gyroscope.
4. Electrodermal activity (EDA) via skin conductance response (SCR) sensor.
5. Cuffless blood pressure (BP) via a bioimpedance sensor or pulse transit time (PTT) estimation and PPG sensor synergy.
6. Cortisol measurements using sweat biochemical sensors.
7. Glucose via PPG sensor or similar sensors

In the current decade, smartwatches with all the above features (sensors) are not unlikely to be released. Further research, improvements, financial expenditure, and firm decisions are required.

Collection, correlation, and data analysis in real time and continually (removing noise and artifacts by constantly resetting the baseline of fluctuating values) using multiple sensors and devices may be challenging. For instance, hormones such as cortisol fluctuate throughout the day. Therefore, determining the baseline measurement of individual and contextual factors with unknown stressors anytime and anywhere is an arduous task.

Introducing diversity in hardware by combining different sensors can significantly increase the complexity of the

hardware, data, and software. However, adding new hardware to an already tested solution or changing the dataset may not guarantee a better performance or prevent it from worsening. Therefore, hardware must be set with appropriate software to achieve optimal performance. Hence, further research and experimentation on hardware and software correlations is required.

The added cost is certain to develop and produce; for example, a smartwatch that combines most of the aforementioned measurements. However, this is a shared cost because the end-user will benefit not only from stress monitoring but also from many other important measurements, such as glucose (very significant for diabetic or pro-diabetic people), blood pressure (for people with BP problems), and health and athletic performance monitoring. Technological enthusiasts are interested in these products.

Legal-ethical issues: Data from wearable devices or sensors for measuring stress may expose personal data of health interest. In other words, they may fall into medical confidentiality. A cardiogram can reveal a disease (e.g., atrial fibrillation or heart attack). EEG can also reveal brain dysfunction (e.g., epilepsy). Therefore, during research, especially when these systems are applied to a large number of people, the consent of the subjects should be required, the privacy of the data should be ensured, and they should be used only for stress measurements (following the 1964 Helsinki Declaration and its later amendments or comparable ethical standards). In addition, attention should be paid to local (region-country) legislation and its particularities.

1. **CONCLUSION**

Stress is a reaction to events or conditions that can be referred to as a stressor. This seriously affects daily life and has a significant impact on human wellbeing. In this study, the most important technological methods using wearable sensors are presented for commercially available products or laboratory/scientific products. Many commercially available user-friendly wearable devices and sensors provide large datasets for analysis, stress detection, and stress management.

This review helped to identify new research areas. Measurement of stress, especially using both the autonomic nervous system (ANS) and hypothalamic–pituitary–adrenal (HPA) axis responses, can theoretically and potentially offer stress detection and pseudo-stress detection optimization.

Data-driven AI involves feeding more data (the more, the better, and up to a certain limit). Data from the distributed sensors were also more abundant and of better quality.

Little to no research has been conducted on the HPA axis and other physical secretions using wearables. Numerous scenarios and combinations (at both the hardware and software data analysis levels) have been developed and researched. Generally, a broader view of the topic is offered

and diversity is encouraged if complexity is welcomed, practically feasible, and economically attractive.

The ultimate aim of a stress detection system is to accurately detect stress, offer a cost-effective commercial solution, and operate under daily life conditions without negatively affecting the individual’s life. This review will assist researchers and scientists in selecting the optimum stress detection method for each daily life scenario, together with the appropriate data analysis method that should be used. The ultimate goals of stress detection and management can be achieved by combining this information.

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