Monitor Mental Health Conditions

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Recently, there has been an increase in the production of devices to monitor mental health and stress as means for expediting detection, and subsequent management of these conditions. The objective of this review is to identify and critically appraise the most recent smart devices and wearable technologies used to identify depression, anxiety, and stress, and the physiological process(es) linked to their detection.

wearable devices smart technology Depression Anxiety Smart device

1. Introduction

Acute stress is a growing, unavoidable issue in contemporary society induced by physical and or emotional stressors, which physiologically can combine to trigger or exacerbate a wide variety of disease states [1][2]. In conjunction with negative emotions such as anxiety and depression, stress can increase cardiovascular disease risk, the leading cause of mortality worldwide [3]. Anxiety disorders are the leading mental health illness, with 264 million affected worldwide [4], with depression projected to be the second major cause of disability in the coming decade [5]. Further, the incidence of these mental health issues is increasingly developing in low- and middle-income countries [4]. Therefore, researchers are trying to create more compact, portable, and accurate technology to monitor stress and mental health status (depression or anxiety). Such devices will ultimately reduce morbidity and the economic burden on the health care system, as patients can seek help earlier or act to reduce symptoms or triggers [6][7].

Vital signs, neural activity (electroencephalogram ((EEG)), heart rate (electrocardiogram ((ECG)), skin temperature, and skin conductance response (electrodermal activity) can provide important information about an individual's health status [8]. However, the challenge is how to make this information more readily available outside of the clinical environment using semi-validated, wearable devices that are tolerated by people and have regulatory approval for their stated purpose [6]. Within the past decade, the creation of commercially available smart devices and wearable technologies to monitor health has grown exponentially [9]. Many smart wearable devices are being developed, including smart textiles, pedometers, wearable EEG systems, smart watches with photoplethysmography, and many other devices that can non-invasively measure several health-related factors [8].However, stress and mental illness are in a different paradigm and often difficult to monitor objectively, with the recent focus on the feasibility of creating technology capable of detection of mental states. Further, research over the last ten years has demonstrated that people are reluctant and find it uncomfortable to wear invasive or large intrusive devices for measuring health status [1][6]. Since smartphones and wearable devices are often carried on one's person as an integral part of life in modern society, they are often chosen as the instruments to detect and monitor stress, anxiety, and depressive symptoms. This review focuses on both bulky wearables and sensor wearables; devices which are tolerable to the wearer, portable, and proposed to be capable of detecting stress, anxiety, and depression.

2. Smart Devices and Wearable Technologies to Detect and Monitor Mental Health Conditions and Stress

2.1. Anxiety

Anxiety is a common mental health issue, particularly in Australia where the prevalence is increasing [10]. It is defined as an unpleasant, emotional response out of proportion to a particular stressor (or even in the absence of), the response of which may or may not be prolonged, resulting in tension and physiological manifestations [11][12]. Episodes of anxiety are triggered from unnecessary stimulation of the hypothalamic–pituitary–adrenal axis, which stimulates the sympathetic limb of the autonomic nervous system (while simultaneously dampening the parasympathetic limb), which results in both psychological and physiological manifestations [11]. Of the latter, alterations in heart rate, respiratory rate and electrodermal activity reflect the function of the sympathetic nervous system [13]. Further, heart rate variability, which is calculated from the R–R interval, has been previously shown to represent the autonomic nervous system activity and is a good marker for stress and anxiety, with anxiety resulting in decreased R–R interval time and increased heart rate due to bolstered sympathetic response and reduced vagal inputs [14][15]. In a recent review by Elgendi and Menon (2019), the validity of using ECG parameters using wearable devices to detect different clinical diagnoses of anxiety was assessed [4]. The overall findings of experimental papers were conflicting and controversial, and the authors concluded that it was challenging to determine the impact ECG features had on determining anxiety with a need for more robust studies moving forward [4]. These cardiovascular measures, as well as respiratory and skin-related measurements, have been incorporated into wearable technologies that were assessed in the studies below.

2.2. Findings of This Review

Four studies [16][17][18][19] were identified for inclusion in this review based on the secondary search term “anxiety”. The study by Balconi et al. (2019) used wearable EEG and ECG (for subsequent HRV computation) devices, including either the Muse™ headband (InteraXon Inc., Toronto, ON, Canada) or the Lowdown Focus glasses (SmithOptics Inc., Clearfield, UT, USA) to determine the effects of mindfulness exercises on both an individual’s objective and subjective levels of stress and anxiety [17]. The study provided minimal detail on which EEG signatures were used on subjects, though the authors suggested that the wearable brain-sensing device has potential for promoting objective stress response by increasing awareness of EEG signatures of dysfunctional hyperactivation [17]. With respect to cardiovascular changes, HRV measures were reduced both at rest and during the stressor task, in conjunction with subjective decrease in stress and anxiety. Reduction of high-frequency components of HRV were found to be useful autonomic measures of the impact of stressors or stress-inducing situations and therefore have implications for the assessment of anxiety and stress [17][20]. Further, reduction in the high-frequency component of HRV (which is a marker of parasympathetic influence on cardiac activity) is consistent with the neurovisceral integration model of stress response [21], which outlines the physiological association between parasympathetic vagal activity and improved executive function (alluding to sympathetic function induced by stress and anxiety, dampening executive function).

Cardiac activity has been the predominant objectively measurable physiological parameter of anxiety in the literature; however, respiratory patterns have been reported to robustly indicate cognitive emotional stress [22][23]. The second article included in the present review, Smith et al. (2020), attempted to measure respiratory rate and variability to compare physiological parameters with subjective scores of anxiety and stress, using the only wearable device (Spire Stone (Spire Health, Stanford, California)) available at the time that could measure these parameters unobtrusively [19]. Despite the capability of the device in measuring respiratory rate and variability, there was a lack of compliance by subjects in the experimental group (they only wore the device 52% of the study days), despite the majority of subjects having reported high tolerability for the device. It was noted that breathing exercises are often implemented to regulate anxiety in people and were not assessed in the biofeedback model of the study [19], which may be worth investigating in the future, as slow, deep breathing is useful in reducing anxiety. The third article included in this review for anxiety, Alberts et al. (2020), also used the Spire Stone (Spire Health, Stanford, CA, USA)) and an adapted version, the Spire Health Tag respiratory monitor (Spire Health, San Francisco, CA, USA). Unlike the study by Smith et al. (2020), the Spire Stone was found to be tolerable in 90.3% of participants, with respiratory rate patterns found to be useful in detection of anxiety and stress [16]. Further studies testing respiratory rate and variability using wearable technology alongside subjective stress and anxiety results are required.

The relationship between the sympathetic nervous system and the integumentary is well-known, with this physiological relationship being used to detect anxiety, stress, and even depression. The fourth study included in the review for “anxiety”, Sano et al. (2018) using two sensors, compared the accuracy of skin conductance (SC), skin temperature (ST), and the three-axis acceleration using the wearable Q-sensor (Affectiva, Boston, MA, USA) and the Motion Logger (AMI, Ardsley, NY, USA) which records activity levels, in detecting mental health conditions and stress, with ST and SC being more useful in detection of stress and mental health conditions [18]. This is unsurprising, as SC has been considered a biomarker for stress [24] and also reflects the level of autonomic arousal, which can provide a stress index during wakefulness. With an accuracy of 87% and 78.3% for detecting poor mental health and depression, respectively, the dual sensor device Q-sensor (Affectiva) was a success in the study by Sano et al. (2018), as one of the first wearable devices to detect stress in a 24/7 daily life setting. Unfortunately, the findings of the three-axis acceleration, which can be used to estimate activity levels and sleep or wake patterns, was not the overall focus of this study [18], though many smart phones currently use this technology, which is useful in detecting depressive symptoms.

2.3. Stress

The bidirectional relationship between emotion and stress is well-known, with many papers reporting the influence emotion has over the autonomic nervous system (Kreibig et al., 2010). The physiological response from acute stress is often protective; however, chronic stress is known to facilitate numerous physical and mental health illnesses, which has a significant economic impact [25][26]. The understanding of chronic stress impact on the body has driven researchers to continue to develop new ways to detect and monitor stress, typically relying on the sympathetic nervous system physiological responses induced by stress, including changes in heart rate, heart rate variability, skin temperature, and conductance (van Kraaij et al., 2020). Algorithms developed based on these well-researched parameters have high accuracy for detecting stress more than 90% of the time in experimental conditions [27][28]. The use of various wearable devices and sensorised garments have been trialled to assess if they can accurately record the physiological responses created by sympathetic nervous system activity, using non-invasive cardiac, respiratory rate, skin conductance, and temperature [2][29].

According to a recent review, heart rate variability is the most studied [6] of all physiological parameters. This study provides a very succinct review of over 60 different wearable technologies, which assess a multitude of different physiological parameters including those mentioned in this review, with the addition of sleep and cognitive function [6]. This review article also contemporaneously reviews which wearable devices have been formally validated for use in research for stress (10%), with only 5% of the wearable technologies listed in the review having been formally validated as capable of accurately detecting health parameters [6].

Electrodermal activity has also gained favour as a marker of sympathetic nervous activity due to its emerging relationship neurophysiologically [30]. Skin conductance responses are associated with the ventromedial prefrontal cortex involved in anticipatory EDA responses, and the amygdala involved in EDA responds to the learned association between stimuli and reinforcement [30], with EDA now seen as an index of attention and not merely a measure of sympathetic activity.

2.4. Findings of This Review

A total of 15 studies were identified for inclusion in this review based on the search term “stress”. Similar to anxiety, the use of cardiac metrics, namely heart rate and heart rate variability, were the predominant physiological markers of stress detection in 10 of the 15 studies which detected stress [9][31][17][25][32][33][34][35][36][26]. It has been reported that altered HRV measurements are related to ANS dysregulation associated with many cardiovascular diseases including cardiac ischemia, myocardial infarction and heart failure, diabetes, and obesity, as well as mental health conditions including anxiety and depression [9][37]. Hernando et al. (2019), with use of the Apple Watch, reported that HRV measurements (in particular R–R interval series) are superior in detecting stress compared to HR alone, with most commercially available devices using average HR, which is heavily controlled by the autonomic nervous system and can also be drastically altered in certain physiological and pathological circumstances [9]. Further, in these situations where there is altered autonomic function (depression), this will be reflected in HRV metrics but not HR alone [38].

In the study by Rodrigues et al. (2020), the Vital Jacket® (1-Lead, Biodevices S.A, Matosinhos, Portugal) was used to assess specific HRV metrics, namely the average of normal-to-normal intervals (AVNN), standard deviation of all normal-to-normal intervals (SDNN), root mean square of differences between successive rhythm-to-rhythm intervals (RMSSD), and low frequency/high frequency (LF/HF) ratio [35]. During stress, AVNN, RMSSD, and the percentage of successive R–R intervals that differ by more than 20 ms (pNN20) decreased, reflecting a depressed HRV, which is the expected response to stress [39]. Additionally, during stress a significant increase in the LF/HF ratio was reported, highlighting the impact of stress on the sympathovagal system [35]. These metrics were useful in identifying stressful situations, and promote the need for the production of quantified occupational health (qOHealth) devices to detect stress, as this study also reported that during stressful episodes, cognitive performance declines.

In the study by Huang et al., the Polar V800 Heart Rate Monitor (Polar Electro OY, Kempele, Finland), which monitors heart rate variability, was validated against ECG HRV under differing stressors, with high correlations. This study found that this wearable device is capable of monitoring stress to the same extent as an ECG, and therefore capable of detecting acute stress [32].

During acute stress, the limbic system and thalamus are activated by the cerebral cortex through the reticular activating system, which subsequently activates the hypothalamus, triggering an autonomic nervous system and endocrine response, resulting in catecholamine and cortisol secretion [40]. In the study by Hong et al. (2010), epinephrine, the stress response hormone, was unsurprisingly reported as having the highest correlation with qualitative stress levels [25]. Moreover, HRV index and LF/HF ratio were surprisingly more accurate in stress detection than cortisol [25], alluding that HRV metrics detected using wearable devices may be superior and more convenient than hormone and neurotransmitter analysis in detecting stress. HRV parameters are reported to be the most reliable in detecting stress, though many devices still use average HR alone, as reported below.

In studies that only examined HR [33][34] it was found that there was a significant difference between genders, with females having significantly higher average HR than males when exposed to occupational stress, when measured using an Apple Watch (Series 1, Apple Inc., Cupertino, CA, USA) [33]. Interestingly, Lucas et al. (2019) also commented that baseline cardiovascular fitness, determined by survey, had no significant impact on HR, which is the inverse of what is physiologically expected [33]. Further, in the study by Pakhomov et al. (2020), which used the Fitbit® (no model specifics provided) to detect HR at baseline and during exposure to stressors, it was found that the Fitbit® is capable of detecting stressors, with HR increasing an average of nine beats per minute [34]. Whilst the findings by Lucas et al. (2019) and Pakhomov et al. (2020) suggest HR may be useful in detecting stress, both studies were limited by the young age of their subjects; thus, the impact of comorbidities on HR, and therefore stress detection, may not be reflective of the general population [33][34]. The study by van Kraajj et al. (2020) supports this, using two separate wearables: an unspecified chest patch for HR measurement and a wristband (Chillband) for detecting activity, with the study reporting that there was a significant relationship between HR and the three-way interaction between chronic stress, gender, and circadian rhythm [26]. Further, it is known that maximum HR decreases linearly with age [41], with sleep and stress levels fluctuating majorly throughout life, which further supports this relationship. The influence of female gender over HR may require wearable devices to have HR scaled to accommodate for this physiological difference, though it appears that HRV metrics may make average HR detection obsolete.

EEG, as an adjunct to HRV in stress detection, was also assessed in two studies [31][17]. Asymmetric analysis of the frequency-band powers in the EEG, measured at the prefrontal cortex, has been previously used to detect stress [42]. The creation of a novel EEG and ECG system capable of simultaneously recording HRV features showed that EEG was more accurate (87.5%) in the detection of stress compared with EEG (77.9%) and HRV (75%) alone, thereby confirming that the simultaneous measurement of the EEG and HRV is more effective for stress detection when combined [31]. Whilst EEG is reported as more sensitive for stress detection in this study, its ability to be incorporated into a compact and visually appealing wearable device is still limited; however, the Muse™ headband is capable of doing this, though its tolerability as a wearable device is not known.

The physiology of the integumentary system in responding to stress is a well-understood phenomenon, with two studies [43][44] incorporating this physiology into a wearable device. Engelniederhammer et al. (2019), who used a sensor smart wristband (Bodymonitor™, Gesis Leibniz-Institute for the Social Sciences, Mannheim, Germany), reported that the EDA is the most simplistic and accurate indicator of emotional arousal, notably stress or aggression [43]. EDA is useful in the detection of stress but may pose challenges with respect to reliability of results in populations who have comorbidities such as diabetes mellitus or hyperthyroidism (though this can be overcome using models as outlined by Kim et al., 2020 [44]). The study by Kim et al. (2020) used a wearable Empatica wristband (E4, Empatica Inc., Boston, MA, USA) which recorded galvanic skin response (GSR) to detect stress in drivers, with an accuracy of 85.3% [44]. Further, the study reported that GSR sensors are currently the preferred method for stress detection, due to ease of setup, its compact nature, and overall simplicity when compared with EGG and ECG [44]. One study performed by Silva et al. (2020), using the Microsoft Smartband 2™, measured HRV in conjunction with skin conductance, which, when incorporated into a machine learning algorithm, could detect stress [36]. Multiple HRV parameters were significantly different during stressful conditions than baseline, notably mean R–R and PSS_{13} scores.

Another study by Seoane et al. (2014) suggested that multiparametric testing (including GSR, temperature, respiratory rate, and ECG) via a prototype wearable garment had superior accuracy in detection of stress than EDA. This formed part of the “Assessment in Real Time of the Stress in Combatants” project [45], which created a wearable garment capable of detecting physical and mental stress within military combat soldiers by monitoring HR, respiratory rate, and EDA [45]. Whilst the wearable device is capable of detecting stress, there was a high rate of error across the metrics, with almost twice as many GSR and skin temperature errors compared with ECG and respiratory rate [45]. This wearable device has prompted other researchers [2] to develop future wearable devices capable of detecting multiple stress-related metrics. In the study by Cho et al. (2017), the research team wanted to create wearable technology that measured photoplethysmograms, electrodermal activity, and skin temperature, with the aim of combining these parameters to accurately detect stress throughout the day [2]. Further, incorporating wearables such as this with feedback solutions to lower stress may aid in reducing the burden stress has on people in everyday life.

In one systematic review, it was found that electrodermal activity is useful in measuring neurocognitive stress, as skin conductance increases when individuals are stressed [46], which reported a wearable not identified with the above search terms. The “shimmer sensor” is a monitoring wearable sensor which uses EDA for stress monitoring, using two finger sensors, capable in one reported study of detecting stress in 86% of subjects; however, HRV and EEG data were also used in detection [46]. An additional study was also found outside of the search criteria which measured EDA to determine the level of pre-surgery stress, using the wrist wearable ADI-VSM (Analog Devices), with an accuracy of 85% [47].

A notable issue with EDA as a means of detecting stress was reported by Anusha et al. (2019), who reported that devices reliant on EDA data are prone to motion artifacts; further, varying pressure exerted on EDA electrodes related to the variable tightness of the wearable and movement of the hand and wrists may also distort the data in a major way, leading to potentially false readings [47].

2.5. Depression

The search term “depression” identified five studies [5][48][49][50][51] which assessed only depression, and one study [18] which assessed “mental health” broadly. EEG is a non-obtrusive, electrophysiological measure of the spontaneous electrical activity in the brain and is widely used to study antidepressant treatment responses due to its availability and low cost [52]. Two studies [5][48] reported the use of EEG in detection or monitoring of depressive symptoms. Cao et al. (2018) tested the response of depressive symptoms to ketamine by analysing EEG changes measured using a wearable forehead EEG device [48], the Mindo-4S Jellyfish (Eee Holter Technology Co. Zhubei District, Hsinchu, Taiwan). The theta and low alpha activity signatures were used as the EEG metrics in this study, which were significantly improved from baseline after ketamine treatment. In terms of neurophysiology, it has been reported that depressive disorders are correlated with a reduction in dorsolateral prefrontal cortex grey matter volumes, as well as unique directional changes in the prefrontal cortex [53]. Li et al. (2015) also used a single-electrode EEG (no specifics provided) to detect depressive symptoms, using specific classifiers, including k-nearest-neighbour (kNN), naïve Bayes (NB), logistic regression (LR), support vector machine (SVM), and random forest (RF) [5]. The kNN performed best out of the outlined classifiers, detecting mild depressive symptoms in 99.1% with the study concluding that a combination of linear and nonlinear EEG features proved to be effective in improving the accuracy of detecting depression; however, the sample size of this study was rather small [5]. One notable advancement in the wearable Mindo-4S Jellyfish by Cao et al. (2018) is the use of dry electrodes and the reduction in preparation time; due to the ease of wearing the device, this may eventuate into a means of monitoring depressive symptoms daily [48].

One study by Zhu et al. (2020) used a 16-channel wearable continuous-wave functional near-infrared spectroscopy (fNIRS) device model 1000 (United States) to measure brain oxy-hemodynamic (HbO) response. The accuracy of the fNIRS in accurate classification of depression was found to be 92.6% [51]. Further, this study also identified mean HbO, full width half maximum, and kurtosis as specific neuro-markers for predicting major depressive disorder across particular brain regions, notably the dorsolateral and ventrolateral prefrontal cortex [51]. The information provided by fNIRS and EEG devices is constantly improving the understanding of depression from a physiological stance, with further investigations of fNIRS in a larger sample size required.

The remaining two studies [25][50] looked at activity levels for the detection of depression using a wearable actigraph watch or smart watch with or without a smartphone. In the study by Zanella-Calzada et al. (2019), real-time measurements of behaviour, feelings, and activity were recorded using an Ecological Momentary Assessment [54], through use of smart phones and an actigraph watch; specifically, the Actiwatch (Cambridge Neurotechnology Ltd., Cambridge, UK, model AW4) [50]. This assessment is necessary for depression monitoring, as most depressive symptom monitoring methods rely on patient reports, which are commonly biased. When blindly selecting depressed subjects from non-depressed subjects, this method accurately detected depressed patients 86.7% of the time [50]. Inversely, it also detected non-depressed subjects in 91.9% of cases. Detecting depression based on the level of physical activity throughout a day through a smartphone may expedite new diagnoses or recurrences in people with depression.

In another study assessing physical activity, Narziev et al. (2020) selected five depression symptom factors which were extracted from the DSM-5 questionnaire, with mood, physical activity, sleep, social activity, and food intake (to ascertain appetite information) and monitored to detect depression using the developed “Short-Term Depression Detector” (STDD) framework, which used smart watch (Galaxy S3) sensors and Android smartphone [49]. Mood was determined by a combination of the above factors using machine learning. For the focus of this review, it was noted that the smart watch used a heart rate monitor and accelerometer to assess physical activity level in subjects, which is typically lower in depression. The study reported that the STDD framework and passive data collection had a strong correlation with the self-reported depression score, with the STDD having an accuracy of 96% in depressive group classification (Narziev et al., 2020). This study highlights the difficulties of objectively recognising depressive symptoms using wearable technologies and promotes the idea of using smartphone apps to gather metrics and qualitative data to assist in detecting depression.

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