Wearable Solutions for Mental Stress Monitoring

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Abstract

Stress significantly impacts both mental and physical health, and wearable devices provide an opportunity for continuous monitoring of physiological variables like heart rate and skin conductance. These devices, coupled with advanced noise and artifact-filtering algorithms, can inform users of health and behavior indicators. The goal of this study was to assess wearable devices for their effectiveness in mental stress monitoring. To achieve this, we conducted a market study, reviewing relevant articles and examining the accessibility of data from available devices. We specifically focused on the Fitbit Sense 2 and Empatica Embrace Plus, evaluating their capabilities in measuring physiological parameters like heart rate and skin conductance. This evaluation also considered the quality of their data processing algorithms and how the raw data can be used for accurate stress measurement.

Keywords— e-Health, biomedical devices, biosensors, signal processing, stress detection

1 Introduction

The World Health Organization (WHO) defines mental health as a state of well-being enabling individuals to cope with life's stressors, work productively, and contribute to their communities [1]. While moderate stress is manageable, chronic stress can be a serious threat to well-being, affecting both mental and physical health. It can disrupt daily life, reduce performance, and contribute to conditions like heart disease, depression, and a weakened immune system [2]. In the workplace, stress is a growing concern, with many workers feeling overwhelmed and seeking better ways to manage it.The WHO encourages finding solutions to reduce and track stress to prevent its escalation and minimize its impact on health..An automated stress detection system can offer timely alerts, allowing individuals to take action before stress reaches critical levels, helping to prevent its negative impact on health and performance.

Cortisol has also been widely used as a biomarker for stress assessment through blood, urine, or saliva samples [3]. However, these measurements are typically conducted in controlled environments, limiting their use for real-time or ambulatory monitoring. To overcome this limitation, other biosignals, such as Electrodermal Activity (EDA) and high rate variability (HRV), have been proposed for stress assessment [4] [5]. EDA, which reflects sympathetic nervous system activation through skin conductance, has been integrated into wearable devices, allowing for continuous and non-invasive stress monitoring. HRV measures the variation in time between heartbeats, reflecting autonomic nervous system balance (sympathetic and para sympathetic), with lower variability indicating higher stress levels [6]. EDA detects changes in skin conductance caused by sweat gland activity, which is directly linked to sympathetic arousal during stress. These signals have traditionally been measured in laboratory settings and have been the subject of numerous studies for stress evaluation. However, today, portable devices allow for continuous measurement of these biosignals, enabling real-time stress monitoring in everyday life. Wearable devices have emerged as innovative tools for monitoring stress continuously in real-life settings offering a more accessible and non-invasive approach to stress assessment [5]. The aim of this study is to identify a wearable device capable of reliably combining HRV and EDA measurements to monitor mental stress. This is particularly important for individuals with pathological conditions, where early detection can lead to targeted therapies. Ideally, such a device should be CE-marked to ensure medical-grade reliability and compliance with regulatory standards, addressing public health concerns by providing a scalable solution for stress management. Additionally, this wearable can be used by individuals for personal stress monitoring, helping them better understand and manage their stress levels in daily life.To achieve this objective, the study is structured as follows: First, existing methods for stress assessment, including biosignals for stress management, are reviewed. Next, available wearable devices capable of measuring HRV and EDA are examined. Finally, their potential applications for stress evaluation are analyzed, considering their effectiveness in real-life settings.

2 Methods

2.1 Sources and Search Strategy

A systematic web search was conducted via Google to identify commercial and professionnels smarwatch or smart rings devices capable of measuring biosignals and acess to data. In cases where specifications were not available in public materials such as websites or datasheets, manufacturers were contacted directly. To track emerging trends, secondary sources like Google Scholar, arXiv, and medRxiv were also consulted. The primary search for relevant studies was carried out in major academic databases such as Scopus, IEEE Xplore, and PubMed, focusing on papers published between 2010 and 2025.

2.2 Questions queries

To systematically analyze wearable devices capable of stress detection, the study aimed to address the following key questions:

1. What are the primary biosignals provided by wearable devices that can be used for personalized stress detection?
2. Which wearable devices on the market can measure both EDA and HRV?
3. Do commercial wearables provide access to raw physiological data, or is the data processed by proprietary algorithms?
4. What are the differences between commercial and professional-grade wearables in terms of stress measurement capabilities?
5. How do battery life, usability, and form factor influence the selection of wearable devices for continuous stress monitoring?

6. Are there publicly available datasets that include HRV and EDA for developing stress detection models?

The market study examined major brands such as Garmin, Apple Watch, Google, and Samsung, along with other manufacturers to ensure a comprehensive overview of available technologies, including both wearable devices like smartwatches and smart rings. Web-based searches were performed using the following queries:

- `"wearable devices" AND "stress monitoring"`
- `"smart ring" AND "biosignals measurement" AND "wearable"`
- `"EDA/HRV" AND "wearable technology"`
- `"mental stress monitoring" AND "wearables"`
- `"sleep monitoringt" AND "wearables"`
- `"professional" AND "medical use" AND "wearable devices"`
- `"related publications" AND "papers" AND "wearable stress monitoring"`

For each wearable device, we researched the corresponding articles, databases, and publications used to monitor mental stresss. The selected papers had to meet the following criteria:

- Public datasets monitoring stress using wearbles devices
- Comparative studies between different wearable devices
- Studies written in English, excluding conference papers and abstracts

3 Results and discussion

3.1 Biomarkers for stress assesment

In the literature, different biosignals have been identified for stress detection: Electrodermal Activity (EDA), Photoplethysmogram (PPG), Electrocardiogram (ECG), body temperature (TEMP), Respiration (RSP), Electromyography (EMG), and Electroencephalography (EEG) [4] [7]. These signals reflect physiological stress responses activated by the sympathetic nervous system and can be captured for real-time monitoring. However, only four of these biosignals EDA, PPG, ECG, body temperature are detectable by a smartwatch or smart rings, making them the most accessible for continuous stress tracking [8].

Additionally, cortisol, a key biomarker of stress, provides valuable insight into chronic stress levels but is primarily measured through blood, urine, or saliva samples in laboratory settings, limiting its use in real-time monitoring [3]. Sleep quality is another important indicator, as stress can significantly impact sleep patterns, and wearable devices increasingly integrate sleep tracking to provide a more comprehensive assessment of an individual's stress levels [9].

A multimodal approach, combining multiple biosignals, has been shown to improve detection accuracy, with more than half of the studies adopting this strategy [10]. Additionally, motion data from accelerometers (ACC) and gyroscopes helps distinguish mental stress from physical stress, improving model accuracy in dynamic conditions. By integrating these diverse signals, wearable devices can provide a more comprehensive and accurate understanding of stress, making it essential to employ devices that combine multiple biosensors, such as EDA, HRV, sleep quality, and others, for effective stress detection and personalized monitoring [11][12].

3.2 Wearables for Biosignals in Stress Detection study

The web research and market analysis revealed that both commercial and medical wearable devices can measure key biosignals necessary for stress detection, including EDA, HRV, heart rate, body temperature, and accelerometry. The analysis focused on three categories: mass-market rings, wrist-worn wearables, and professional/medical devices. These devices track various signals, with sleep quality identified as an important parameter for stress evaluation. Device autonomy was also crucial for continuous monitoring, which led to the exclusion of rings for long-term use.

The Table 1 summarizes these findings, showing the device type, integrated sensors, and whether sleep quality is measured. HRV is a core feature in most wearables, with sleep quality monitoring also being common [9]. Electrodermal activity is less widely implemented, although some devices include it (Table 1). In response to the second research query, "Which wearable devices on the market can measure both EDA and HRV?", two wrist wearables identified were the Fitbit Sense 2 and the EmbracePlus by Empatica (formerly Empatica E4) (Figure 1). These two devices represent the current solution for continuous stress monitoring, combining both EDA and HRV measurement. However, Empatica and Fitbit devices feature a battery life of up to 7 days, allowing for continuous monitoring

To answer the question: Do commercial wearables provide access to raw physiological data, or is the data processed by proprietary algorithms? The Fitbit Sense 2, while a popular and accessible option, does not provide raw data. According to a report from the University of Twente in 2023, Fitbit provides the following data access via its web application, though it is available only through a premium subscription:

- **EDA**: Fitbit's Sleep Log provides EDA data every 30 seconds. However, the data is aggre-

Device (Company)	**Biosignals**	**Sleep Quality**
	Rings	
Oura Ring (Oura)	HRV, ACC, TEMP	Yes
Happy Ring (Happy)	HRV, EDA, ACC	Yes
	Mass Market Wrist-Worn Wearables	
Samsung Galaxy Watch 6	PPG, TEMP, ACC	No
Apple Watch (Apple)	HRV, ACC	Sleep
Garmin (Garmin)	HRV, ACC	Some
Fitbit Sense 2 (Fitbit)	HRV, EDA, ACC, TEMP	Yes
Whoop 4.0 (Whoop)	HRV, ACC	Yes
	Professional/Medical Wrist-Worn Wearables	
EmbracePlus (Empatica)	HRV, EDA, ACC, TEMP	Yes
ActivInsights (ActivInsights)	HRV, ACC	No

Table 1: Wearable devices measuring biosignals with sleep quality

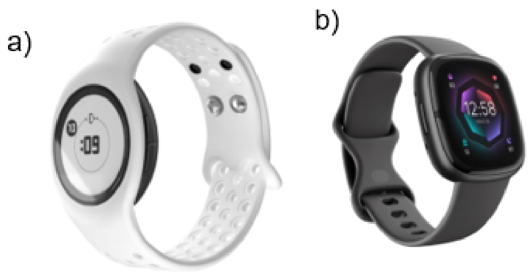

Figure 1: a) Embrace Plus by Empatica [13] b) FitBit Sense 2 [14]

gated into a score that is available only every 30 seconds, which can only be retrieved upon request from the provider. This makes it less useful for real-time analysis or highly detailed stress detection models.

- **HRV** : The HRV data is provided through a query called "HRV Intraday," which returns a JSON file containing metrics like RMSSD, high-frequency power, and low-frequency power. However, these data points are only available during the sleep phase, limiting their scope for stress detection outside of this context. The RMSSD (Root Mean Square of Successive Differences) is a widely used HRV parameter that reflects short-term heart rate variability, providing insights into parasympathetic nervous system activity. Users must correlate ECG (electrocardiogram) and PPG (photoplethysmogram) signals to estimate the RR interval, which is necessary to calculate HRV. Access to this HRV data is available every 10-15 seconds, though interruptions in the data collection may occur.

- **Sleep Data**: Fitbit's "Sleep Log" request returns a JSON file with detailed information about sleep, including date, time, sleep stages, and duration. While this data is useful for general sleep monitoring, it is not available at very short intervals (such as every second), limiting its potential for real-time analysis of physiological signals. Instead, the data is aggregated into 10-15 second intervals, which may not provide the granularity needed for in-depth stress research.

In contrast, EmbracePlus by Empatica offers a broader range of data, including EDA and HRV, and provides access to raw data, making it an ideal choice for researchers in clinical or research settings. This capability allows for more accurate analysis of stress responses.

The EmbracePlus provides the following sampled biosignals:

- **ACC**: Sampled at 64 Hz
- **EDA**: Sampled at 4 Hz (S)
- **PPG**: Sampled at 64 Hz
- **Skin temperature**: Sampled at 4 Hz (°C)

3.3 List of public datasets

The literature review identified six public datasets using Empatica E4 devices to measure stress, but none of the datasets mentioned in the review utilize the Fitbit Sense 2 specifically. Indeed, studies were conducted using the Empatica E4, but it has been retired. The Embrace Plus is the latest model available, offering similar medical-grade features. [13]. The datasets EmpathicSchool [15], WESAD [11], PASS [16], and AffectiveROAD [17], A Multimodal Sensor Dataset for Continuous Stress Detection of Nurses in a Hospital [10] and ACTIVES [18] primarily focus on stress detection using Empatica sensors, including EDA, PPG, ECG, and other physiological signals.

These datasets cover various types of stress, including cognitive, social, mental, occupational, gaming, and driving stress. The studies were conducted either under controlled experimental conditions or in real-life scenarios (e.g., hospital work or driving).

Populations vary from general healthy individuals to specific groups such as nurses (during COVID-19), clinical samples, and school children. The sample sizes range from 10 to 48 participants, with some datasets showing gender and age biases. Commonly used sensors include EDA and PPG, often combined with other sensors like ECG, skin temperature, and accelerometrie enhance stress detection accuracy.

3.4 A Comparative study comparing Fitbit Sense et Empatica E4

The study by Ronca et al [19] compared the reliability of wearable devices Fitbit Sense, Empatica E4, and Shimmer GSR3+ in measuring autonomic parameters, specifically EDA, against laboratory reference equipment. The devices used for measuring EDA were the Shimmer GSR3+ (64 Hz), Empatica E4 (4 Hz), and Fitbit Sense (1 measurement every 30 seconds), with the signals from the research devices being filtered at 1 Hz.

The placement of the devices varied: the Shimmer GSR3+ was placed on the fingers, the Empatica E4 was worn on the wrist, and the Fitbit Sense required palm-to-device contact. The study found that the Empatica E4 showed good reliability and strong correlation with the reference equipment. However, the Fitbit Sense had limited reliability, particularly in heart rate measurements. While individual correlations for skin conductance were weak, the overall analysis suggested potential for improvement.

The Empatica E4 showed good reliability and strong correlation with reference equipment, making it a better choice for medical applications, particularly for chronic stress monitoring. In contrast, the Fitbit Sense 2, though useful for well-being and fitness tracking, showed limited reliability, especially in heart rate measurements. Thus, for medical applications, the Empatica E4 is a better option.

4 Conclusion

The aim of our study was to assess wearable devices capable of measuring key biosignals for stress detection, including EDA and HRV. Two devices emerged as particularly notable for their continuous EDA measurement capabilities: the Fitbit Sense 2 and the EmbracePlus by Empatica. While both offer valuable health monitoring features, the EmbracePlus is more suited for research and clinical use due to its access to raw data and its CE marking, which ensures compliance with health standards, making it ideal for patient monitoring or clinical studies. Furthermore, Empatica has been widely used in research studies, and several datasets are available, reinforcing its credibility and applicability in academic and clinical settings.

In contrast, the Fitbit Sense 2, a mass-market device, offers health features such as heart rate monitoring, HRV tracking, and a "Stress Management Score." However, its data access is limited to pre-processed values with a fixed sampling frequency (SCL measured every 30 seconds). While it provides useful information for basic health tracking, its lack of raw data access and the constraints of its sampling frequency make it less suitable for more detailed or personalized stress detection models.

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