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Wearables devices for monitoring psychophysiological stress: a narrative review

Dispositivos Vestíveis para monitoramento psicofisiológico do estresse: uma revisão narrativa

Abstract

Wearable devices use sensors that continuously capture physiological signals and, once processed, allow the monitoring and development of interventions in various areas of health, including mental disorders. In Clinical Psychology, this type of technology can cooperate to the objective and continuous measurement of stress, as well as to generate feedback when stressful situations occur. This narrative literature review focused on these devices, presenting the main scientific data available, as well as opportunities and difficulties in implementing these devices in stress assessment and health treatments. The reviewed research indicated that it is necessary to develop more robust and theoretically based systems that integrate physiological, subjective and contextual responses to implement this type of wearable in clinical contexts. However, the accuracy already demonstrated by wearable sensors in laboratory situations and some continuous monitoring tests, reinforce that these are tools with great potential for application in clinical psychological practice.

Keywords: physiological stress; psychological stress; monitoring; wereable electronic devices.

Resumo

Dispositivos vestíveis utilizam sensores que capturam sinais fisiológicos continuamente e, uma vez processados, permitem o monitoramento e o desenvolvimento de intervenções em diversas áreas da saúde, incluindo os transtornos mentais. Na clínica, esse de tipo de tecnologia pode contribuir tanto na mensuração objetiva e contínua do estresse quanto gerar *feedbacks* quando ocorrem situações estressantes. Esta revisão narrativa da literatura enfocou esses equipamentos, apresentando os principais dados científicos disponíveis, além de oportunidades e dificuldades na implementação desses aparelhos na avaliação do estresse e em tratamentos de saúde. As pesquisas revisadas indicaram que é necessário o desenvolvimento de sistemas mais robustos e teoricamente fundamentados que integrem respostas fisiológicas, subjetivas e contextuais para a implementação desse tipo de dispositivo em contextos clínicos. No entanto, a acurácia já demonstrada por sensores vestíveis em situações laboratoriais e alguns testes de monitoramento contínuo reforçam que estas são ferramentas com grande potencial de aplicação na prática da clínica psicológica.

Palavras-chave: estresse fisiológico; estresse psicológico; monitoramento; dispositivos eletrônicos vestíveis.

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INTRODUCTION

Stress is a natural and functional phenomenon for the preservation of the species, consisting in a psychophysiological response to the internal or external stimuli perception of threat (Boonstra, 2013). When a threat interrupts the organism's homeostasis, alterations in the autonomic nervous system trigger fight-or-flight reactions, increasing the individual's chances of survival. In Psychology, it is understood that stress is the result of something perceived as threatening which add a subjective component of the stressor's cognitive assessment that triggers a series of psychophysiological effects. Therefore, the same stressful event can be interpreted differently by people and produce different stress reactions (Otaran et al., 2018).

When the individual's response to the stressful event does not occur adaptively, the stress situation is persistent or the stress reaction remains for a long time, it can start to cause damage, inducing a process of chronic stress that also generates an oxidative stress response on a biological level (Kauer-Sant'Ana et al., 2011). Chronic stress is associated with the development of physical and mental health problems, including cardiovascular disease, depressive and anxiety disorders (Cohen et al., 2007). Thus, psychophysiology can contribute through the development of measuring ways and analyzing measures related to stress supporting prevention and intervention strategies (Can et al., 2019).

The dynamics of stress responses are mediated by the Hypothalamus-Pituitary-Adrenal (HPA) axis, which releases a series of responses through the nervous, endocrine, and immune systems. The HPA axis regulates the release of cortisol through the adrenal gland, and this hormone is a glucocorticoid that helps with physiological stress reactions.

Physiological stress reactions, in turn, are regulated by the Autonomic Nervous System, which comprises the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). Changing the balance between these systems implies physiological responses causing changes in heart rate, digestion and sweating, some characteristics of stress (Bear et al., 2017). The physiological changes related to stress can be identified from several biomarkers (Gee et al., 2016; Henriques et al., 2011) and, consequently, be measured in different ways. In this sense, the aim of this study was to carry out a narrative review on the use of these biomarkers for measuring stress, with special emphasis on the development and use of wearables devices. The term "wearable device" is used to define portable technological devices that use sensors capable of monitoring physiological data and thus providing continuous information about the user's health (Schüll, 2016; Soh et al., 2015). In this sense, the possibilities and limitations of the psychophysiological assessment of stress will be addressed. Afterwards, the conceptual aspects, scientific evidence, and challenges in wearable research for the application of monitoring in the context of clinical psychology will be discussed.

PSYCHOPHYSIOLOGICAL STRESS ASSESSMENT

Psychophysiology investigates the relationship between psychological and physiological variables, considering the interaction of brain, body, and environment (Andreassi, 2007). Among several potentials for interdisciplinary collaboration in this field (Hughes et al., 2018), the study of physiological markers for stress monitoring as, for example, electrocardiogram, electrodermal activity, electromyography, and electroencephalography, is a promising one (Henriques et al., 2011).

The physiological measure most associated with stress is the electrocardiogram (ECG) (Kim et al., 2018), which allows the measurement of heart rate and heart rate variability (HRV), in addition to other parameters associated with the PNS and to the SNS (Valenza et al., 2018). Activation of the SNS, resulting from the presence of a stressor, increases heart rate. HRV refers to the variation in the R-R intervals (highest point of activity of the cardiac cycle) and indicate the interval between one heartbeat and another (De Witte et al., 2019) and it has various causes such as changes in breathing rhythm, physical, behavioral, and emotional changes. Unlike heart rate, a higher HRV indicates the ideal interaction among SNS and PNS (Lagos et al. 2008). Therefore, HRV is sensitive to the identification of alterations in the SNS and PNS in stressful situations. However, HRV parameters are still used with caution due to their limitations, such as being influenced by many variables, as noise and individual physiological patterns, and it should also be considered that subjective perception and health aspects can also affect these data decreasing its specificity in the context of clinical evaluations (Kim et al., 2018).

Another measure that receives a lot of attention is electroencephalography (EEG), which records the electrical activity of brain cells. The EEG can detect five different brain rhythms: delta, theta, alpha, beta and gamma. These rhythms are different levels in terms of electrical signals measured in hertz, correlated with states such as deep sleep, emotions, relaxed state, focused attention and information processing. The EEG is influenced by aspects such as age, behavior, attention, metabolic disorders, and medication (Blinowska & Durka, 2006).

The Electrodermal Activity (EDA) refers to the skin's ability to conduct electricity. The sensors, in this case, assess the electrical activity of sweat glands that do not have parasympathetic innervation, a measure being exclusively influenced by the activation of the SNS, which, by producing more sweat, increases the electrical conductivity of the skin (Posada-Quintero & Chon, 2020). Other measures used in some studies are skin temperature, usually associated with blood pressure and being influenced by factors external and internal to the body, in addition to electromyography, which measures the electrical signals (hertz) emitted during muscle contraction and the higher, greater muscle tension in that region, which may be associated with physical exertion or tension due to stress, for example (Shaffer & Neblett, 2010).

Increasing evidences associating psychophysiological reactivity patterns with mental disorders or emotional conditions allow us to glimpse a potential advance in terms of assessment in the field of psychology, adding more objective measures to evaluation processes based exclusively on the patient's self--report (Seppälä et al., 2019). Moreover, psychophysiological data enable a wide range of interventions so that patients can recognize triggers and physiological reactions associated with emotions and behave with greater awareness of these processes. These forms of applicability are presented and discussed below.

THE EVALUATION OF PSYCHOPHYSIOLOGICAL STRESS MARKERS AND THEIR APPLICATION IN CLINICAL HEALTH PSYCHOLOGY

Biofeedback is one of the most used tools in the context of clinical treatment that has the support of psychophysiology. Derived from psychophysiology and influenced by different areas such as behavioral therapy, behavioral medicine, stress research and intervention strategies, biomedical engineering, among others, the biofeedback approach emerged in the United States in the 1960s (Miller, 1969). Biofeedback refers to a technique to capture psychophysiological measurements and provide visual or auditory feedback to the individual. Psychophysiological measurements are captured by sensors that send information to an electronic monitoring device (computer software or mobile device application), which processes the data to provide instant feedback to the user. This technique is based on the principle that as individuals become more aware of their maladaptive psychophysiological responses, they gain more control over their physiological and emotional state (Schoenberg & David, 2014).

Biofeedback can be used both for stress management in the non-clinical population (Yu et al., 2018) and for the treatment of anxiety disorders, insomnia and migraine, for example, showing evidence of symptom cutback and clinical improvement (Goessl et al., 2017; Lantyer et al., 2013). Nevertheless, further clinical studies are needed to reinforce the usefulness of this approach (Gee et al., 2016). Literature reviews investigating the use of biofeedback to anxiety and stress management show that most studies use the HRV indicator and reach good results to identify stress and intervene in symptoms (De Witte et al., 2019; Lantyer et al., 2013).

At the same time, biofeedback devices have important limitations, considering that they often need to be connected by wires to computers or provide feedback for a limited time, not being applicable to people's routine, but to specific tasks or activities. Thus, the biofeedback approach still requires interventions to be applied in more controlled contexts, such as the office, to result in reliable measures and often have high cost or require training for their use, not being practical for use in routine situations (Yu et al., 2018).

In the past few years, technological advances in the development of biosensors have allowed techniques, such as biofeedback, to employ devices with better accessibility, portability, practicality, comfort, and quality of data collected. This has enabled the use of biofeedback devices as a data source to continuously monitor the physiological state, using sensors in wearable devices (Kamišalić et al., 2018). Some of these wearable sensors consist of low-cost devices that provide good quality signals (Attaran et al., 2018; Betti et al., 2017; Saha et al., 2018). Thus, new application and intervention possibilities associated with physiological measures are emerging, considering the increasing efficiency of the platforms that integrate these data (Can et al., 2019; Kamišalić et al., 2018).

CONCEPT AND APPLICATIONS OF WEARABLE DEVICES

Wearable devices use technology to monitor individuals' physiological responses during their daily lives. These devices are composed of sensors that, in contact or close to the skin, are able to collect physiological data that provide a variety of health information, such as heart rate (Schüll, 2016; Soh et al., 2015). Along with applied computing resources, wearable devices collect physiological data that is analyzed to identify different patterns of responses. Thus, these devices are paired with applications and collect information in real time, providing an immediate response to the user (Li et al., 2016). The development of wearable systems is leveraging changes in health care models, making it possible to continuously monitor individuals and customize treatments and preventive strategies (Servati et al., 2017; Zhou, 2020).

Currently, wearable devices can be found in the form of watches and even clothes that are connected via Bluetooth to smartphones and are often associated with more elaborate applications, capable of collecting, processing, and integrating physiological signals. The applications, generally known as mHealth, have the potential to modify the way we monitor and treat mental disorders (Seppälä et al., 2019), since they can be used to provide online feedback to the user and expand their involvement with the tool in their daily lives (Yu et al., 2018). Therefore, the physiological data provided by the sensors can be collected online by mobile devices, which can support applications to detect specific states and generate interventions to be followed by users (Jebelli et al., 2018). This technology, applied to the health area, has received several names, such as Wearable Wireless Health Monitoring (Soh et al., 2015) and Wearable/Attachable Health Monitoring (Wang et al., 2017). Wearables must be portable and easy to use. But, above all, they offer advantages in terms of continuous collection of physiological data in an ecological environment, using advanced computational techniques to detect patterns or changes in these data and enabling a personalized assessment of the individual, aiming at interventions tailored to their needs. The possibility of continuous monitoring of physiological patterns, movement and contextual data allow a wide range of application of these technologies, inside and outside the psychological clinic, helping professionals and individuals in promoting mental health and emotional regulation (Can et al., 2019; Smets et al., 2018).

The use of wearable devices as tools to monitor stress is closely associated with computational advances in the area of Machine Learning and Artificial Intelligence and allow modeling and predicting states of stress based on the detection of patterns in recorded physiological data (Niemann et al., 2018; Sano & Picard, 2013). It is understood that the continuous assessment of physiological states associated with stress throughout the day has the potential to increase our understanding of stress response patterns, in addition to allowing the identification of antecedents and triggers for the development of diseases, especially psychological ones. This resource can complement and integrate psychological care, considering that, during treatment, continuous monitoring can increase patients' emotional awareness, being a means for symptom tracking and monitoring, and to broaden our understanding of thought patterns, emotions, behaviors and physiological reactions (Sharmin et al., 2015).

As can be seen, there are many clinical possibilities for the use of wearable devices associated with applications, including aspects of assessment, treatment, and health prevention strategies (Miller, 2012). Access to mobile devices anytime and anywhere allows interventions via mHealth (mobile applications that monitor or intervene in mental health, or "mental health") to be carried out in situations of significant risk or suffering (Lui et al., 2017), which can increase the user's motivation and engagement in the treatment and enable therapeutic action during crisis (Christmann et al., 2017).

Also known as M-health apps, this type of tool is related to a software for health care (physical or mental) available on mobile devices such as smartphones or tablets (Marcolino et al., 2018). Wearable devices (Lee et al., 2019) and M-health applications (Marcolino et al., 2018) are emergent technologies that have potential applications in psychology. Even both technologies can work in an integrated way, wearable devices, and m-health applications can be developed and used independently. M-health does not require integration with physiological signals, although they are an excellent feedback tool, given the continuous monitoring promoted by wearable devices. Among the different uses, these applications enable the recording of relevant information for the treatment and can provide brief behavioral interventions, such as relaxation techniques (Wang et al., 2018).

Wearable devices are considered a recent technology with potential for application in the health area, as some studies have already shown. For example, they are being used in the home rehabilitation of people with chronic diseases such as Parkinson's (Soh et al., 2015) or for monitoring patients admitted to hospitals (Lee et al., 2019). In the future, there is the possibility of integrating information with databases from health systems, opening the way to data linkage, as well as for the standardization of clinical protocols. However, in order to reach these advances, a set of studies is needed, from different areas, so that these devices compose a quality and ethically acceptable information system (Piwek et al., 2016). Therefore, wearable devices constitute a recent and promising field of basic and applied research in the health area in general. In particular, the literature points to a growing interest in studies on the development of wearable devices for continuous monitoring of psychophysiological responses related to stress (Can et al., 2019; Giannakakis et al., 2019).

STUDIES OF PSYCHOPHYSIOLOGICAL MEASURES AND APPLICATIONS OF WEARABLE DEVICES FOR CONTINUOUS STRESS ASSESSMENT

Studies related to the use of wearable devices for the physiological assessment of stress can be organized into two groups. The first one focuses on research carried out under laboratory conditions with variable control, to try to obtain reliable data on the stress response (Rodrigues et al., 2018; Schmidt et al., 2018). The second set of studies refers to data collection in an ecological environment, in order to obtain information from natural situations, such as during sleep (Muaremi et al., 2014), in traffic (Rodrigues et al., 2015), in a work environment (Hernandez et al., 2011) or during daily situations (Adams et al., 2014; Sano & Picard, 2013), helping to develop assessment approaches with high external validity.

Most studies assess physiological stress responses in the laboratory (eg. Rodrigues et al., 2018; Schmidt et al., 2018), while continuous assessment during daily life is still incipient. Studies aimed to assess stress continuously, in an ecological context, have become of interest to the scientific field only in the last decade, considering that the technology to support such investigations has emerged recently. The most used measures in these conditions are ECG, EDA and skin temperature (see Table 1). A piece of data that complements the physiological measurements, commonly used, is the accelerometer (ACC), which indicates whether the individual is at rest or moving, making it possible to filter whether the physiological response is due to a stressful event or to locomotion. The main studies on wearable devices that we were able to review are described in Table 1. It should be noted that most of them included the non-clinical population, except for the study from Kikhia et al. (2018), who monitored elderly people with dementia. A detail of particular interest refers to the area of researchers who carry out these studies, most linked to the areas of technology, with an exception being the study by Smets et al. (2018), which had

Table 1. Description of studies on continuous stress assessment using wearable devices.

No.* and Authors	Country	Objective	Psychophysiological measurements	Sample
1. Hernandez et al. (2011)	US	Assess Psychophysiological stress in call center workers	EDA	Adults (N=9)
2. Sano and Picard, (2013)	US	Assess stress throughout the day	ACC, EDA, contextual data (eg. call)	Adults (N=18)
3. Adams et al. (2014)	US	Assess stress levels in daily life	EDA and tone (voice)	Adults (N=10)
4. Muaremi et al. (2014)	Switzerland	Assess stress levels based on nocturnal sleep patterns	ACC, ECG, EDA, Breath, Body posture, ST	Adults (N=10)
5. Hovsepian et al. (2015)	US	Develop a stress detection model	ACC, ECG e PPG	Eco sample (N=20) and in laboratory (N=26)
6. Kikhia et al. (2018)	Sweden	Monitor stress and sleep in elderly people with dementia	ACC, EDA, sleep sensor	Elderly with dementia (N=04)
7. Rodrigues et al. (2015)	Portugal	Develop stress detection system for drivers	ACC, ECG and location (GPS)	Adults (N=36)
8. Gjoreski et al. (2017)	Slovenia	Monitor everyday psychological stress	ACC, BVP, EDA, ECG and ST	Adults (N=21)
9. Smets et al. (2018)	Belgium	Develop stress detection system	ACC, ECG, EDA and ST	Healthy Adults (N=1002)
10. Can et al. (2019)	Turkey	Develop a stress detection system in the daily routine	ACC, EDA, PPG and ST	Adults (N=21)
11. Han (2019)	US	Develop a stress detection system in the daily routine	PPG, ECG and EDA	Adults (N=17)
12. Pratap et al. (2020)	US	Assess stress at a wellness retreat (before during and after)	ECG	Adults (N=112)
13. Rosa and Yang (2019)	US	Assess stress during physical activity and mental arithmetic task	ECG, EDA, ST and Bio moviment	Adults (N=5)

Note. No.*= number assigned to the study in the present review; ACC: Accelerometer; BVP: *Blood volume Pressure*; ECG: Electrocardiogram (including Heart Rate and Heart Rate Variability); EDA: Electrodermal Activity; PPG: Photoplethysmography; ST: Skin Temperature

the participation of authors from the field of psychology and neurosciences.

Table 1 also indicates that most studies were carried out in countries in Europe and North America. Most of these studies had used multiple measurements in small samples. Their objectives were generally to test, in the laboratory or in an ecological context, systems that were accurate in identifying psychophysiological stress patterns. In Table 2, we present the main procedures and results of the reviewed studies.

Despite being an emerging area of research, it is important to consider that there are many gaps in studies that seek to develop devices capable of monitoring stress throughout the day. According to Gjoreski et al. (2017), it is a challenging problem, considering that stress is highly subjective; it is difficult to define the onset, duration and intensity of each stressful event and that stress must simultaneously assess three components: physiological, emotional, and behavioral response. Furthermore, it is still a challenge to develop computational models capable of differentiating physiological stress responses from those arising from physical activity, changes in posture, sudden movements, hot weather (Hovsepian et al., 2015) or from changes caused by emotions such as happiness or euphoria (Schmidt et al., 2018).

Although there are devices already being marketed on the market with the purpose of monitoring physical activity and sleep, for example, the application of this resource reliably to psychophysiological assessment, and with therapeutic applicability, is still difficult (Soh et al., 2015; Wang et al., 2017). One of the initial challenges for the use of wearable devices was the cost of these sensors. Currently, wearable sensors consist of low-cost devices that provide good quality signals (Attaran et al., 2016; Betti et al., 2017; Saha et al., 2018). Another technical challenge that initially presented itself was the use of platforms to provide feedback to the patient. However, the widespread use of mobile devices by the general population presents the possibility of collecting, processing, and integrating these physiological signals with increasingly elaborate applications. Currently, physiological data provided by sensors can be collected online by mobile devices, which can support applications to detect specific states and generate interventions for users to follow (Jebelli et al., 2018; Schmidt et al., 2018). On the other hand, in developing countries, lower health literacy and more difficult access to smartphones and minimally adequate internet access can constitute important barriers in the scalability and equity of

Table 2. Results of studies on Continuous Assessment of Stress Using Wearable Devices.

Ref.*	Method	Main results
1.	Physiological data were evaluated and compared with subjective perception in 1,500 calls in call centers.	78.03% accuracy for stress assessment during stressful calls.
2.	Stress levels in the daily routine were assessed. Data were associated with self-report information such as stress levels and sleep quality.	75% accuracy for detecting low and high stress levels.
3.	Physiological data were collected during the daily routine for seven days, also using Likert scales for subjective assessment of stress.	EDA and voice data correlated with subjective stress assessments, the latter being important for sensor calibration.
4.	Data was collected from 136 participants' sleep sessions, which indicated their perception of stress every night using the PSS scale.	73% accuracy in identifying low, medium and high stress levels, compared to PSS responses.
5.	Two studies: (1) inside lab, with cognitive and physical stress (cold water); (2) ecological study using sensors for seven days.	89% accuracy in laboratory situations and 72% in the ecological context.
6.	The participants were monitored for four months, in two elderly resting homes.	Use of sensors has been well accepted and can help staff manage patients.
7.	Drivers had physiological data recorded during 145 hours of work. Data was correlated with traffic intensity, identified by GPS.	75% of stressful situations occurred in places with low visibility, narrow roads and during traffic violations.
8.	Participants monitored for 55 days, collecting data in their context.	70% accuracy in stress detection with physiological data. When adding context information, the accuracy rose to 95%.
9.	Participants monitored continuously for five consecutive days, with daily recording of information about symptoms and health behaviors via smartphone. They used a stress-inducing task (MIST) and an emotional response scale (SAM) for calibration.	Strong associations between physiological signals and contextual information. Associations between levels of anxiety and depression with physiological stress responses.
10.	Data collection during nine-day periods, in situations such as lectures, exams and during free time.	Accuracy of 88.20% in detecting the three conditions (lecture, exams and free time) with different stress levels.
11.	Collection during daily routine.	Accuracy of 81.82% in daily settings.
12.	Participants were monitored for seven days before, during and one month after the wellness retreat.	Strong associations between physiological signs (decrease in HR and increase in HRV) and the context of intervention.
13.	Collection during physical activity and online arithmetic.	89% overall accuracy when performing various activities.

Note. Ref.*: study number in Table 1; MIST: Montreal Imaging Stress Task; PSS: Perceived Stress Scale; SAM: Self-Assessment Manikin; HR: Heart Rate; HRV: Heart Rate Variability

interventions using wearables for continuous stress monitoring (Goodday & Friend, 2019).

In addition to the methodological difficulties in achieving the goal of continuous stress assessment, the device's design and usability represent another challenge. Wristwatches are often used, as it is a minimally invasive area (Ollander et al., 2016). However, the location for collecting physiological data, in this case, is not always the most appropriate or that provides the best data (Hovsepian et al., 2015). In addition, due to the constant movement of the arms, assessment with wearable wrist devices produces many undesirable artifacts in the physiological record, which makes it difficult to reliably detect stress through biosensor signals. A good alternative could be wearable devices that are placed in the chest region, as they demonstrate greater reliability for collecting data, although they are less practical for everyday use (Gilgen-Ammann et al., 2019). Still, the possibility of data loss through wireless transmission is still a challenge and needs improvement by developers (Hovsepian et al., 2015). Ways of dealing with movement artifacts and pattern identification in an ecological environment are already being studied and developed (Zhou, 2020). These and other challenges must be overcome for these devices to be accepted by the community at large and for health professionals to be able to incorporate them into health treatments (Soh et al., 2015; Wang et al., 2017).

Thus, in addition to the technological development of wearable devices for continuous monitoring and automatic stress detection, it is important that these data can be used not only for assessment, but also in interventions with clinical populations, in order to improve existing treatments. It is understood that there is great potential for the use of this technology in clinical contexts. On the one hand, it is a possibility to improve psychological assessment, currently performed largely through clinical investigation and questionnaires, which can suffer from subjective and idiosyncratic biases. In this sense, if there are biomarkers that can be detected by wearable device systems, there is a possibility of making the assessment of mental disorders more precise and individualized. Complementarily, the interventions used can benefit from the physiological response obtained. For example, exposure techniques used in the treatment of disorders such as anxiety, Posttraumatic Stress, and Obsessive-compulsive and can rely on physiological feedback to see if they are generating the necessary response and to control the intensity of exposures. Thus, associated with relaxation and emotional regulation techniques, they can rely on visual feedback, obtaining greater clarity of physiological reactions and facilitating the achievement of therapeutic goals.

Although the proposals combining continuous stress detection and psychotherapeutic interventions are recent, authors have discussed this possibility. Smets et al. (2018) propose the use of automatic stress detection data in combination with stress control interventions. Reimer et al. (2017) consider the use of these devices relevant for the treatment of craving in patients with chemical dependency. However, as far as we could verify, we did not find any studies applying such proposals and investigating the complete cycle from stress detection, during continuous monitoring, to intervention proposals, which is a path for our research (Can et al., 2019). In addition to technological aspects, areas such as psychology and related areas can contribute to the development of wearable devices, as they can provide theoretical and applied support on stress, psychopathology, and clinical care, facilitating their implementation for therapeutic purposes.

CONCLUSION

Wearable devices systems for assessment and intervention in stress and associated clinical conditions suffer the same challenges as other research in this area. Despite presenting an opportunity for personalized health assessment and prevention, they face difficulties in relation to scalability, types of materials to be used for the continuous use of sensors, considering body locations for data collection, material flexibility, comfort and practicality, artifacts in the physiological record generated by the users' movements, which can interfere with the signals obtained and undermine the reliability of these data, in addition to the security and privacy of the information, which need to be preserved and kept only for the user and the healthcare professional that accompanies him.

The growing technological development of sensors has potential for the health area, especially for Psychology. The use of these for assessment and treatment in clinical psychology, especially studies aimed at assessing stress through wearable devices, may be a promising possibility in the search for more objective measures of assessment and integration of physical and psychological aspects. These devices may also be an important resource for intervention in Psychology, both from the point of view of prevention in mental health and in clinical treatment, in order to complement and enrich strategies that are already well-established in the area. Furthermore, it opens the way for new interventions in search of health and well-being that effectively impact people's emotions and behavior. This seems a likely future for health technology and the first steps are already being taken by several researchers in different countries, and mental health and psychology would not be left out of such changes.

REFERENCES

Adams, P., Rabbi, M., Rahman, T., Matthews, M., Voida, A., Gay, G., ... Voida, S. (2014, July 27). *Towards personal stress informatics: Comparing minimally invasive techniques for measuring daily stress in the wild* [article]. 8th International Conference on Pervasive Computing Technologies for Healthcare (pp. 72-79). https://doi.org/10.4108/icst.pervasivehealth.2014.254959

Andreassi, J. L. (2007). *Psychophysiology: Human behavior and physiological response* (5th ed.). Lawrence Erlbaum.

Attaran, N., Puranik, A., Brooks, J., & Mohsenin, T. (2018). Embedded low-power processor for personalized stress detection. *IEEE Transactions on Circuits and Systems II: Express Briefs, 65*(12), 2032-2036.

Bear, M. F., Paradiso, M. A., & Connors, B. W. (2017). *Neurociências: Desvendando o sistema nervoso*. Artmed.

Betti, S., Lova, R. M., Rovini, E., Acerbi, G., Santarelli, L., Cabiati, M., ... Cavallo, F. (2017). Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers. *IEEE Transactions on Biomedical Engineering, 65*(8), 1748-1758. https://doi.org/ 10.1109/TBME.2017.2764507

Blinowska, K., & Durka, P. (2006). Electroencephalography (EEG). In M. Akay (Ed.), *Wiley encyclopedia of biomedical engineering*. Wiley. https://doi.org/10.1002/9780471740360.ebs0418

Boonstra, R. (2013). The ecology of stress: A marriage of disciplines. *Functional Ecology, 27*(1), 7-10. https://doi.org/10.1111/1365-2435.12048

Can, Y. S., Arnrich, B., & Ersoy, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *Journal of Biomedical Informatics, 92*, 103-139. https://doi.org/10.1016/j.jbi.2019.103139

Christmann, C. A., Hoffmann, A., & Bleser, G. (2017). Stress management apps with regard to emotion-focused coping and behavior change techniques: A content analysis. *JMIR MHealth and UHealth, 5*(2), 1-12. https://doi.org/10.2196/mhealth.6471

Cohen, S., Janicki-Deverts, D., & Miller, G. E. (2007). Psychological stress and disease. *The Journal of the American Medical Association, 298*(14), 1685-1687. https://doi.org/10.1001/jama.298.14.1685

De Witte, N. A. J., Buyck, I., & Van Daele, T. (2019). Combining biofeedback with stress management interventions: A systematic review of physiological and psychological effects. *Applied Psychophysiology Biofeedback, 44*(2), 71-82. https://doi.org/10.1007/s10484-018-09427-7

Gee, B. L., Griffiths, K. M., & Gulliver, A. (2016). Effectiveness of mobile technologies delivering Ecological Momentary Interventions for stress and anxiety: A systematic review. *Journal of the American Medical Informatics Association, 23*(1), 221-229. https://doi.org/10.1093/jamia/ocv043

Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2019). Review on psychological stress detection using biosignals. *IEEE Transactions on Affective Computing*, 1-22. https://doi.org/10.1109/TAFFC.2019.2927337

Gilgen-Ammann, R., Schweizer, T., & Wyss, T. (2019). RR interval signal quality of a heart rate monitor and an ECG Holter at rest and during exercise. *European Journal of Applied Physiology, 119*(7), 1525-1532. https://doi.org/10.1007/s00421-019-04142-5

Gjoreski, M., Luštrek, M., Gams, M., & Gjoreski, H. (2017). Monitoring stress with a wrist device using context. *Journal of Biomedical Informatics, 73,* 159-170. https://doi.org/10.1016/j.jbi.2017.08.006

Goessl, V. C., Curtiss, J. E., & Hofmann, S. G. (2017). The effect of heart rate variability biofeedback training on stress and anxiety: A meta-analysis. *Psychological Medicine, 47*(15), 2578-2586. https://doi.org/10.1017/S0033291717001003

Goodday, S. M., & Friend, S. (2019). Unlocking stress and forecasting its consequences with digital technology. *NPJ Digital Medicine, 2*(1),1-5. https://doi.org/10.1038/s41746-019-0151-8

Han, H. J. (2019). *Objective stress monitoring based on wearable sensors in everyday settings* [doctoral thesis]. University of California. https://escholarship.org/uc/item/16v1t1ft

Henriques, G., Keffer, S., Abrahamson, C., & Horst, S. J. (2011). Exploring the effectiveness of a computer-based heart rate variability biofeedback program in reducing anxiety in college students. *Applied Psychophysiology Biofeedback, 36*(2), 101-112. https://doi.org/10.1007/s10484-011-9151-4

Hernandez, J., Morris, R. R., & Picard, R. W. (2011). Call center stress recognition with person-specific models. *ACII 2011: Affective Computing and Intelligent Interaction, 1,* 125-134. https://doi.org/10.1007/978-3-642-24600-5_16

Hovsepian, K., Al'Absi, M., Ertin, E., Kamarck, T., Nakajima, M., & Kumar, S. (2015, September). *cStress: Towards a gold standard for continuous stress assessment in the mobile environment*. 15th ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 493-504).

Hughes, B. M., Steffen, P. R., & Thayer, J. F. (2018). The psychophysiology of stress and adaptation: Models, pathways, and implications. *International Journal of Psychophysiology,* 131, 1-3. https://doi.org/10.1016/j.ijpsycho.2018.06.003

Jebelli, H., Khalili, M. M., & Lee, S. (2018). A continuously updated, computationally efficient stress recognition framework using electroencephalogram (EEG) by applying online multitask learning algorithms (OMTL). *IEEE Journal of Biomedical and Health Informatics, 23*(5), 1928-1939. https://doi.org/10.1109/JBHI.2018.2870963

Kamišalić, A., Fister, I., Turkanović, M., & Karakatiĉ, S. (2018). Sensors and functionalities of non-invasive wrist-wearable devices: A review. *Sensors (Switzerland)*, *18*(6), e1714. https://doi.org/10.3390/s18061714

Kauer-Sant'Anna, M., Brietzke, E., & Quevedo, J. (2011). Psiconeuroendocrinologia. In F. Kapczinski, J. Quevedo, & I. Izquierdo (Eds.), *bases biológicas dos transtornos mentais* (3. ed., pp. 55-76). Artmed.

Kikhia, B., Stavropoulos, T. G., Meditskos, G., Kompatsiaris, I., Hallberg, J., Sävenstedt, S., & Melander, C. (2018). Utilizing ambient and wearable sensors to monitor sleep and stress for people with BPSD in nursing homes. *Journal of Ambient Intelligence and Humanized Computing, 9*(2), 261-273. https://doi.org/10.1007/s12652-015-0331-6

Kim, H. G., Cheon, E. J., Bai, D. S., Lee, Y. H., & Koo, B. H. (2018). Stress and heart rate variability: A meta-analysis and review of the literature. *Psychiatry Investigation, 15*(3), 235-245.

Lagos, L., Vaschillo, E., Vaschillo, B., Lehrer, P., Bates, M., & Pandina, R. (2008). Heart rate variability biofeedback as a strategy for dealing with competitive anxiety. *A Case Study. Biofeedback, 36*(3), 109-115. https://doi.org/10.5298/1081-5937-39.1.11

Lantyer, A. da S., Viana, M. de B., & Padovani, R. C. (2013). Biofeedback no tratamento de transtornos relacionados ao estresse e à ansiedade: Uma revisão crítica. *Psico-USF*, *18*(1), 131-140. https://doi.org/10.1590/s1413-82712013000100014

Lee, U., Han, K., Cho, H., Chung, K. M., Hong, H., Lee, S. J., & Carroll, J. M. (2019). Intelligent positive computing with mobile, wearable, and IoT devices: Literature review and research directions. *Ad Hoc Networks, 83*, 8-24. https://doi.org/10.1016/j.adhoc.2018.08.021

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics, 88*, 8-17. https://doi.org/10.1016/j.ijmedinf.2015.12.010

Lui, J. H. L., Marcus, D. K., & Barry, C. T. (2017). Evidence-based apps? A review of mental health mobile applications in a psychotherapy context. *Professional Psychology: Research and Practice, 48*(3), 199-210. https://doi.org/10.1037/pro0000122

Marcolino, M. S., Oliveira, J. A. Q., D'Agostino, M., Ribeiro, A. L., Alkmim, M. B. M., & Novillo-Ortiz, D. (2018). The Impact of mHealth Interventions: Systematic review of systematic reviews. *JMIR MHealth and UHealth, 6(*1), 1-11. https://doi.org/10.2196/mhealth.8873

Miller, G. (2012). The smartphone psychology manifesto. *Perspectives on Psychological Science*, *7*(3), 221-237. https://doi.org/10.1177/1745691612441215

Miller, N. (1969). Psychosomatic effects of specific types of training. *Annals of the New York Academy of Sciences*, *159*(3), 1025-1040. https://doi.org/10.1111/j.1749-6632.1969.tb12995.x

Muaremi, A., Bexheti, A., Gravenhorst, F., Arnrich, B., & Troster, G. (2014). Monitoring the impact of stress on the sleep patterns of pilgrims using wearable sensors. *International Conference on Biomedical and Health Informatics,* 185-188. https://doi.org/10.1109/BHI.2014.6864335

Niemann, M., Prange, A., & Sonntag, D. (2018, June 18-21). *Towards a Multimodal Multisensory Cognitive Assessment Framework* [article]. 2018 IEEE 31st International Symposium on Computer-Based Medical Systems. doi: 10.1109/CBMS.2018.0001210.1109/CBMS.2018.00012

Ollander, S., Godin, C., Campagne, A., & Charbonnier, S. (2016). *A comparison of wearable and stationary sensors for stress detection* [article]. 2016 IEEE International Conference on Systems, Man, and Cybernetics (pp. 4362-4366). https://doi.org/10.1109/SMC.2016.7844917

Otaran, P., Castro, E. K. de, & Remor, E. (2018). Estresse e distresse emocional. In E. K. de Castro, & E. Remor (Orgs.), *Bases teóricas da psicologia da saúde* (pp. 165-180). Appris.

Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The rise of consumer health dispositivos vestíveis: Promises and barriers. *PLoS Medicine*, *13*(2), e1001953. http://doi.org/ 10.1371/journal.pmed.1001953

Posada-Quintero, H. F., & Chon, K. H. (2020). Innovations in electrodermal activity data collection and signal processing: A systematic review. *Sensors (Switzerland), 20*(2), e479. https://doi.org/10.3390/s20020479

Pratap, A., Steinhubl, S., Neto, E. C., Wegerich, S. W., Peterson, C. T., Weiss, L., … Mills, P. J. (2020). Changes in continuous, long-term heart rate variability and individualized physiological responses to wellness and vacation interventions using a wearable sensor. *Frontiers in Cardiovascular Medicine, 7*, e120. https://doi.org/10.3389/fcvm.2020.00120

Reimer, U., Laurenzi, E., Maier, E., & Ulmer, T. (2017). *Mobile stress recognition and relaxation support with smartcoping: User-adaptive interpretation of physiological stress parameters* [article]. 50th Hawaii International Conference on System Sciences. https://doi.org/10.24251/hicss.2017.435

Rodrigues, J. G. P., Kaiseler, M., Aguiar, A., Cunha, J. P. S., & Barros, J. (2015). A mobile sensing approach to stress detection and memory activation for public bus drivers. *IEEE Transactions on Intelligent Transportation Systems, 1*6(6), 3294-3303. https://doi.org/10.1109/TITS.2015.2445314

Rodrigues, S., Paiva, J. S., Dias, D., Aleixo, M., Filipe, R., & Cunha, J. P. S. (2018). A wearable system for the stress monitoring of air traffic controllers during an air traffic control refresher training and the trier social stress test: a comparative study. *The Open Bioinformatics Journal, 11*(1), 106-116. https://doi.org/10.2174/1875036201811010106

Rosa, B. M. G., & Yang, G. Z. (2019). A flexible wearable device for measurement of cardiac, electrodermal and motion parameters in mental healthcare applications. *IEEE Journal of Biomedical and Health Informatics, 23*(6), 2276-2285. https://doi.org/10.1109/JBHI.2019.2938311

Saha, S. S., Rahman, S., Rasna, M. J., Islam, A. M., & Ahad, M. A. R. (2018). *DU-MD: An open-source human action dataset for ubiquitous wearable sensors* [article]. 7th International Conference on Informatics, Electronics & Vision (ICIEV) (pp. 567-572). https://doi.org/10.1109/ICIEV.2018.8641051.

Sano, A., & Picard, R. W. (2013). *Stress recognition using wearable sensors and mobile phones* [article]. 2013 Humaine association conference on affective computing and intelligent interaction (pp. 671-676). https://doi.org/10.1109/acii.2013.117

Schmidt, P., Reiss, A., Dürichen, R., Marberger, C., & Van Laerhoven, K. (2018). *Introducing WESAD, a multimodal dataset for wearable stress and affect detection* [article]. 18th International Conference on Multimodal Interaction (pp. 16-20). https://doi.org/10.1145/3242969.3242985

Schoenberg, P. L. A., & David, A. S. (2014). Biofeedback for psychiatric disorders: A systematic review. *Applied Psychophysiology Biofeedback, 39*(2), 109-135. https://doi.org/10.1007/s10484-014-9246-9

Schüll, N. D. (2016). Data for life: Wearable technology and the design of self-care. *BioSocieties, 11*(3), 317-333.

Seppälä, J., De Vita, I., Jämsä, T., Miettunen, J., Isohanni, M., Rubinstein, K., … Bulgheroni, M. (2019). Mobile phone and wearable sensor-based mHealth approach for psychiatric disorders and symptoms: Systematic review and link to the M-REsist project. *Journal of Medical Internet Research, 2*1(2), 1-14. https://doi.org/10.2196/mental.9819

Servati, A., Zou, L., Wang, J., Ko, F., & Servati, P. (2017). Novel flexible wearable sensor materials and signal. *Sensors, 17*(7), e1622. https://doi.org/10.3390/s17071622

Shaffer, F., & Neblett, R. (2010). Practical anatomy and physiology: The skeletal muscle system. *Biofeedback, 38*(2), 47-51. https://doi.org/10.5298/1081-5937-38.2.47

Sharmin, M., Raij, A., Epstien, D., Nahum-Shani, I., Beck, J. G., Vhaduri, S., … Kumar, S. (2015). Visualization of time-series sensor data to inform the design of just-in-time adaptive stress interventions. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 344*, 505-516. https://doi.org/10.1126/science.1249098.Sleep

Smets, E., Rios Velazquez, E., Schiavone, G., Chakroun, I., D'Hondt, E., De Raedt, W., … Van Hoof, C. (2018). Large-scale wearable data reveal digital phenotypes for daily-life stress detection. *NPJ Digital Medicine, 1*(1). https://doi.org/10.1038/s41746-018-0074-9

Soh, P. J., Vandenbosch, G. A. E., Mercuri, M., & Schreurs, D. M. M. P. (2015). Wearable wireless health monitoring: Current developments, challenges, and future trends. *IEEE Microwave Magazine, 16*(4), 55-70. https://doi.org/10.1109/MMM.2015.2394021

Valenza, G., Citi, L., Saul, J. P., & Barbieri, R. (2018). Measures of sympathetic and parasympathetic autonomic outflow from heartbeat dynamics. *Journal of Applied Physiology*, *125*(1), 19-39. https://doi.org/10.1152/japplphysiol.00842.2017

Wang, K., Varma, D. S., & Prosperi, M. (2018). A systematic review of the effectiveness of mobile apps for monitoring and management of mental health symptoms or disorders. *Journal of Psychiatric Research, 107*, 73-78. https://doi.org/10.1016/j.jpsychires.2018.10.006

Wang, X., Liu, Z., & Zhang, T. (2017). flexible sensing electronics for wearable/attachable health monitoring. *Small, 13*(25), e602790. https://doi.org/10.1002/smll.201602790

Yu, B., Funk, M., Hu, J., Wang, Q., & Feijs, L. (2018). Biofeedback for everyday stress management: A Systematic review. *Frontiers in ICT*, *5*(23), 1-22. https://doi.org/10.3389/fict.2018.00023

Zhou, X. (2020). Wearable health monitoring system based on human motion state recognition. *Computer Communications, 150*, 62-71. https://doi.org/10.1016/j.comcom.2019.11.008