Assessment of Stress Levels using technological tools: A Review and Prospective Analysis of Heart Rate Variability and Sleep Quality Parameters

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Abstract

"Stress overload" (SO) represents an imbalance where psychosocial, work, environmental, or health-related burdens exceed an individual's adaptive capacity, engendering negative physical and mental health outcomes. This study reviews tech tools, focusing on Heart Rate Variability (HRV) and metrics for sleep quality analysis (SA) i.e. the number of nocturnal awakenings (NNA). Modern technologies for measuring HRV and NNA could enhance the traditional stress detection methods, respectively from the neuropsychologist by the "Stress Overload Scale" (SOS) and polysomnography (PSG) by the neurophysiology technician. Notably, they also allow continuous monitoring, and may curtail healthcare costs. Employing Machine Learning (ML) on smartwatches using photoplethysmography (PPG) HRV accuracy achieves 98.10-98.18%. Wearable devices also exhibit strong sensitivity and specificity for measuring NNA. In children distinct nocturnal movement patterns should be considered. While HRV correlates directly with stress levels, poor SA indicates only a 4.7 fold increased risk of SO. HRV's integration into allostatic load assessments is advocated. However clinical validation is necessary, while potential privacy concerns may arise, as electrocardiography (ECG) signals can potentially uniquely identify patients. Synthesizing HRV solely from photoplethysmography (PPG) data obtained from wearable devices offers an economical and practical approach, although it may be less accurate than HRV from ECG guided by Respiratory Rate (RR). The latter requires additional hardware, i.e. ECG sensor and either Respiratory Inductive Plethysmography or Respiratory Impedance Plethysmography. However, modern smartwatches possess sufficient computational power to perform ML inference, making them capable of improving PPG-based HRV estimation. By leveraging comprehensive datasets capturing signals like plethysmography, ECG, HRV, and RR, alongside sleep metrics, it will be possible to develop refined algorithms to increase the accuracy of stress risk prediction and its level. Continuous monitoring may support nursing diagnosis of SO, enhancing early intervention and its evaluation.

Keywords

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Heart Rate Variability (HRV), Number of Nocturnal Awakenings (NNA), Nursing diagnosis, Stress Overload (SO), disturbed sleep pattern, sleep quality analysis (SA), wearable and wireless technology, Artificial Intelligence (AI), “Mozart effect”.

1. Introduction

Psychological stress has been shown to be a powerful trigger of neuroinflammation [1],[2] through the dysregulation of the gut microbiome [3], and neuroinflammation may be involved in the onset of neurodegenerative diseases [4],[5].

Stress impacts various vital parameters including blood pressure, HR, HRV, cortisol levels, and glycemia, eventually leading to the onset of many serious diseases including depression and vascular inflammation [6]. The authors Viljoen, M., & Claassen et ali compared allostatic load and HRV as health risk indicators [6]. The findings revealed that these two methods provided comparable results. The study recommended that total HRV and vagal measures should be included in allostatic load assessments, and suggested further exploration of the role of heart rate responses to orthostatic stress in these assessment. Moreover stress is also associated with declarative memory decline [7].

Various categories of individuals have been highlighted in literature as being at risk of SO, such as caregivers of seriously ill patients [8], health workers subjected to mobbing [9], night shift workers [10], or up to the association of long working hours with the onset of cardiovascular diseases [11], and the correlation between night work, particularly in nursing, and the increased risk of certain types of cancer [12].

In the global scenario of the criticalities caused by the COVID-19 pandemic and the concurrent reduction of nursing resources observed internationally, both in hospital and community settings, the stress overload experienced by healthcare personnel has been documented through increased anxiety, sleep disturbances [13] and suicidal ideation [14].

For the reasons listed above, monitoring stress levels in individuals considered at risk is of paramount importance.

The recent clinical validation by NANDA-I (North American Nursing Diagnosis Association-International) of progressively more precise nursing diagnoses raises the need for nurses to use technological tools for accurate measurements in the process of nursing diagnosis [15]. The NANDA-I has validated numerous nursing diagnoses in this area of interest, including the following:

- "Stress Overload" (SO),
- "anxiety" (Nursing Care Plan already published),
- "Disturbed sleep pattern",
- "Sleep deprivation",
- "Stress urinary incontinence".

Nurses play an important role in increasing the number of SO diagnoses, contributing to the early activation of specific prevention programs for anxiety and stress. Therefore, providing nursing staff with technological tools for accurate measurements in this area becomes a priority.

Given the lack of a short review in the literature that synthesizes the use of non-invasive new technologies capable of monitoring stress levels and identifying individuals at risk of SO, this work provides a brief overview of the use of HRV (Heart Rate Variability) and sleep quality analysis (SA) measured through wearable devices.

Specifically, the work is organized as follows:

Section 2 explains the rationale behind the use of these technologies for continuous monitoring.

Section 3 describes the research strategy and inclusion criteria.

Section 4 provides a comprehensive review of stress detection, and in general, emotion monitoring. Initially, the focus was on defining stress, starting from Russell's pioneering work. Then, given the need for continuous and non-invasive monitoring of individuals at risk of stress overload, non-invasive technologies that allow for continuous monitoring of stress levels and early risk diagnosis were reviewed.

Section 5 presents a brief literature review focused on the available technological tools for capturing movement during sleep using accelerometers, up to the current state of the art for detecting total sleep time, number of wrist movements during the night, and duration of sleep and wakefulness phases using

miniaturized accelerometers and gyroscopes, for sleep pattern analysis.
Section 6 illustrates the findings.
Section 7 focuses on the limitations of technological tools.
Section 8 presents further considerations, suggesting the evaluation of the Mozart effect through wearable and wireless technology in patients with neurodegenerative diseases, aiming to include it in nursing care plans related to SO diagnosis, hypothesizing that such non-invasive intervention may be associated with the significant improvement in Nursing outcomes in terms of reduction in the degree of stress and anxiety. Section 9 provides the conclusions and directions for future research.

2. Background

The COVID-19 pandemic has imposed the need for continuous home monitoring by family and community nurses, so providing innovative technological tools for nurses is more urgent than ever.
In the latest years, nursing diagnoses related to the cognitive aspect of the patient have begun to be based on techniques validated in the literature [16],[17]; on the contrary, there is a significant lack of research regarding objective metrics for the assessment of nursing diagnoses related to the alteration of the psychological aspect of the patient, such as SO or sleep disturbance. Furthermore, there is a lack of rigorous scientific evaluation of the variation of vital parameters in relation to the emotional state, including the levels of SO, which is inversely proportional to the HRV-Index [18]. In fact, recent research shows that HRV decrease correlates with an increase in stress levels [19],[20].
Finally, the increasing use of technological tools has the actual potential to increase the early monitoring of the onset of many serious disease through the rilevation of HRV as a health risk indicator among the routinely measured parameters.

3. Search Strategy

To obtain a comprehensive exploration of this topic, its development, and the future opportunities, we decided to search Scopus , MEDLINE (OVID, Ebsco), and Science Direct databases as well as Google Scholar search engine.
The search terms comprised: Heart Rate Variability (HRV), “stress overload”, neuroinflammation, Respiratory Rate (RR), emotion analysis through electrocardiography, number of nocturnal awakenings (NNA), miniaturized accelerometers and gyroscopes, micro mechanicals systems (MEMS) sensors, “sleep pattern analysis”, "disturbed sleep pattern", wearable and wireless technology, nursing diagnosis.
Search terms were used to identify potential articles. A comprehensive review of titles, abstracts, and keywords was conducted to assess the eligibility of the studies according to the inclusion criteria.

Inclusion criteria
The following inclusion criteria were used for this brief literature review:
a) articles published in international peer-reviewed journals with an impact factor of at least Q2 concerning the technical analysis.
b) Accessibility, digital or scanned.
c) English language.
d) Before March 2023.
e) With a sole focus on the analysis of stress levels or predictive factors of stress (e.g. sleep disturbances).
f) Regarding the technological aspect, the focus was on articles published in engineering journals where information and communication technologies intersect with healthcare.

4. Impact of Stress on Heart Rate Variability (HRV) and its measurement.

The techniques described in the literature for emotion detection are varied and not always easily applicable in hospital settings [20],[21],[22]. Conversely, studies focused on the analysis of signals from single-lead ECG detected from the wrist using wearable technologies such as smartwatches allow for a combination of ease of use, low costs, and high levels of accuracy [23].

HRV measures the variability of the distance between heartbeats (RR intervals) in the time domain, expressed in milliseconds. These characteristics are considered one of the most widely used and effective methods in ECG-based emotion recognition systems [19], [24],[25],[26].

HRV is recognized as a non-invasive measure of the regulation of the autonomic nervous system (ANS) of the heart [19]. Spectral analysis of HRV shows two main components: a high-frequency band (HF) (from 0.15 Hz to 0.4 Hz) and a low-frequency band (LF) (from 0.04 to 0.15 Hz). The true measure of stress based on the HRV signal is represented by the degree of sympathetic branch arousal of the sympathetic nervous system (SNS), through normalized power in the low-frequency (LF) signal band and sympathetic-vagal balance (LF/HF ratio). Since both the sympathetic and parasympathetic branches of the ANS are reflected in the HRV signal, preprocessing is necessary. This preprocessing involves filtering the signal using a low-pass filter, which reduces the overestimation of high frequencies (HF), typical of the parasympathetic branch, making the estimation of stress levels more reliable [19].

The authors in [19] demonstrated that HRV alone is not a statistically significant parameter for stress assessment. However, it becomes significant when analyzed in the frequency domain. The authors used respiratory rate (RR)-guided HRV. The analysis is first performed by calculating the Fourier transform on the signal, which means transitioning from the time domain to the frequency domain, and then generating the 2D Fourier spectrogram of the frequency of the preprocessed HRV signal over time. Therefore, to obtain a n accurate HRV, it is essential to include RR data in the algorithm, which can be detected from the single-lead ECG signal from the wrist.

Furthermore, RR is widely accepted as the most discriminative index for stress classification (accuracy = 88.2%), based on the detection of significantly higher and less stable RR during stress phases compared to relaxation phases [19]. Conversely, a randomized controlled study [27] demonstrated how non-invasive stress reduction interventions, such as music therapy, can remodel RR.

The wearable device presented in Figure 1 is the underside of a smartwatch capable of sampling peripheral blood oxygen saturation (SpO2) data, heart rate, and ECG signals, through which HRV value is calculated. Additionally, the average RR can be calculated from the ECG signal. The work by [28] shows a possible implementation. However, the detection of RR-guided HRV based on six signals originating from the single-lead ECG from the wrist/finger requires the user to remember to periodically place their index finger of the opposite wrist, on the conductor plate of the smartwatch. In addition to the micro mechanicals systems (MEMS) sensors included in the smartwatch presented in Figure 1, other devices are available for HRV calculation, such as, a chest-strap built in ECG sensor, which nevertheless does not incorporate miniaturized accelerometers and gyroscopes, which would provide additional information in a multimodal analysis of stress levels.

Figure 1. The underside of the wearable device is capable of sampling SpO2 (infrared light signal), HR (green light signal computed from the raw PPG signal) and ECG, through which HRV can be calculated; it includes a triaxial accelerometer.

The latest applications of emotion classification based on single-lead electrocardiogram (ECG) waveforms are based on the theories of Russell. The author defined human emotion along three dimensions: valence, arousal, and dominance [29], [30]. The most recent applications of AI that make use of artificial neural networks are based on these dimensions. The valence dimension measures whether a human is experiencing negative or positive feelings, the arousal dimension measures whether a human feels bored or excited, while the dominance dimension measures whether a person feels low or high control over his/her actions. The range defined for each dimension goes from 1 (very low) to 5 (extremely high). Each dimension has gradients of values that determine various emotions such as anxiety, fear, stress, joy, and so on.

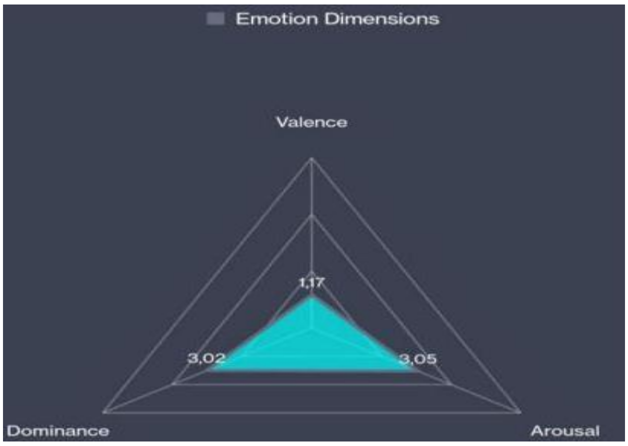

Figure 2. Emotion analysis through ECG along three dimensions.

In 2017 the authors [31] presented a dataset comprising ECG and EEG signals with associated emotion annotations based on Russell's dimensions. This dataset, called DREAMER, has been used by several authors as a reference dataset for estimating emotions solely from the ECG signal by comparing the associated annotations. Specifically, (Nita, S., 2022) developed a convolutional neural network (CNN) and achieved an accuracy rate of 95.16% for valence, 85.56% for arousal, and 77.54% for dominance.
These results are very promising, but they do not reach the levels of the gold standard reference for assessing stress, namely the Stress Overload Scale (SOS) [32] proposed by Amirkhan J.H., that demonstrated excellent sensitivity (96%) and specificity (100%) in the classification of a sample (n=231) from the general population [33]. Furthermore, in order to obtain clinical validation of SO detection using a convolutional network based on HRV and RR data extracted from the ECG waveform, a comparison with the results obtained through the administration of the SOS by a neuropsychologist on the same sample of participants would be necessary.
The study [34] suggests that the Number of Skin Conductance (SC) fluctuations may be an additional method for monitoring the perioperative stress. Nevertheless it is based on a very small sample and and it is not generalizable to all stressors.
Finally the article "Automatic and Intelligent Stressor Identification Based on Photoplethysmography Analysis" [35] presented a new technique and model for stress and stressors detention, outperforming the current state-of-the-art.
A stressor is any environmental factor that causes a person to feel pressured or threatened, triggering the body's fight-or-flight response. Both biological and psychological sources of stress have been identified.
Photoplethysmography (i.e. a low-intensity infrared light photodetector that detects changes in cardiac activity) or PPG data, a subset of heart rate data, is gathered by smartwatches and may be used to assess a wide range of physiological states. The interbeat interval (IBI) and blood volume pulse (BVP) are first

extracted from the time-series PPG data, and then the data is translated into 2D spatial pictures. After collecting this information, 2D pictures are created.
For the purpose of identifying stress and stressors, the 2D pictures of IBI-BVP data are input into a Convolutional Neural Network (CNN) and an Extra Trees Classifier, both of which are ML models. Based on the average pixel intensity of the pictures, the constructed model correctly diagnosed stress with an average accuracy of 98.10% when using the CNN and 99.18% when using the Extra Trees Classifier. In addition, it accurately classified stressors as either physical, cognitive, or social 98.5 percent of the time when using the CNN and 96.4 percent of the time when using the Extra Trees Classifier. Current best practices for stressor identification have been surpassed by these findings. From a practical standpoint, the stress detection based on PPG (Photoplethysmography) includes the advantage of continuous measurements without the user having to remember to place opposite wrist index finger on the single-lead ECG plate sensor. The PPG signal is captured automatically and in background without having the user to perform any kind of action. However, devices that have enough computational power to run advanced ML algorithms such as extra trees (ensemble learning) are more expensive when compared to non-AI algorithms.

5. Relationship between sleep quality and stress levels

Examples of nursing diagnoses pertaining to other states triggering SO, are sleep pattern disorder, sleep deprivation syndrome, and possible stress urinary incontinence (U.I). The planning of intervention for stress overload associated with disturbed sleep patterns should therefore initially exclude physiological problems such as UI, in order to implement specific treatments such as pelvic floor rehabilitation and active motor activity. The study [36] suggests indeed that UI itself may be a trigger of both insomnia and nocturnal agitation in people with Alzheimer's disease and related dementia (ADRD); this is due to progressive neuronal death and the resulting sensory deficit in sensing a full bladder to the point of being unable to express the request to be accompanied to the toilet preferably before going to sleep or if the urge to urinate occurs during sleep. UI in people with ADRD is therefore also associated with interrupted sleep and restlessness also in caregivers [37]. Best available evidence suggests that insomnia is bidirectionally related to anxiety [38]; in contrast, studies examining correlations between insomnia and stress are rare in the literature.

The study [39] investigated the correlation between sleep quality and levels of stress among academic students in Indonesia, reporting a significant relationship between sleep quality and level of stress among a sample of 450 students ($p = 0.001$; $\alpha = 0.05$). Students with poor sleep quality had a 4.7-fold increased risk of having higher stress levels, if compared to students with good sleep quality.
Despite the absence of a direct relationship between poor sleep quality and stress, abnormalities in the sleep pattern represent a warning signal and may identify people at risk of SO.

5.1 Capturing and measuring the number of nocturnal awakenings

Nocturnal awakenings may be extracted automatically using several kinds of sensors: most used sensors are accelerometers and gyroscopes as well as standard RGB video by means of computer vision [40].

Accelerometers and gyroscopes:

Prior to the development of micro and nanotechnology, the number of nocturnal awakenings with technological instruments was only made possible by the use of uncomfortable accelerometers mounted on the patients: these devices provided relevant information mainly to determine the orientation and acceleration parameters [41]. Accelerometers store the variability of acceleration in time on the three dimensions over time (x,y,z), [40].

Computer Vision techniques (Video Cameras):

Within AI techniques, computer vision refers to the set of methods that use cameras and image processing techniques to capture relevant information from the surrounding environment and objects (including people). To analyze human body movements, historically, one or more cameras are used in conjunction with various image processing techniques (such as noise removal) with the aim of extracting relevant information.

Among the most successful techniques, the Infrared Thermography, which makes use of temperatures of the human body, has among the highest accuracy rates with about 91% [42]. In recent years, human pose estimation from video clips has been another emerging field of gait analysis [42], [43]. These technologies make use of deep learning techniques to extract information about body parts from video frames, i.e., for each video frame extracting the coordinates of each body joint [44]. Specifically Dentamaro et al. in [42] used pose estimation and computer vision techniques, as well as machine learning and the Kinematic Theory of Rapid Human Movement [45] for the pathological classification of certain types of movements from video recordings. Similar approaches were used also in [44] for timely fall detection and alert as well as novel deep learning techniques [46]. The frontier of computer vision for human activity recognition allows for the prevention and detection of different types of activities involving movements (including violence) to which nurses are subjected particularly in emergency departments [47].

Wireless and wearable sensors:

With the development of nanotechnology, wearable and wireless sensors that enable the calculation of RR, and, based on it also HRV, as well as SA, are increasingly embedded within low-cost smartwatches. Specifically, regarding to the elaboration of SA wireless and wearable sensors such as MEMS sensors that allow the detection of the number of nocturnal movements from the wrist, and duration of sleep-wake phases using miniaturized accelerometers and gyroscopes, for sleep pattern analysis [48],[49].

Indeed, wearable accelerometers and gyroscope sensors contained in modern smartwatches (as the one in Fig.1) detect signals from the patient and send them, at predetermined time intervals, to the patient's personal smartphone. Then the software installed on the smartphone, after the analysis phase, may send the data to a server that stores the data inside a general database used by the multidisciplinary team. The enhancement of such devices and the provision of them for family nurses may be relevant for the implementation and support of remote and continuous home care.

A further development of this research aims at improving sleep quality based on the data provided by wearable and wireless devices [50].

The current evaluation of the performance of wearable sleep trackers has been made possible comparing it versus polysomnography (PSG), currently considered the gold standard method [51],[52].

As shown by Pesonen, A. et al. in [53], wearable devices have shown excellent sensitivity (> 0.91) and adequate specificity (> 0.77) when compared to PSG analysis on detecting the wake after sleep onset (WASO) which is used to compute the number of nocturnal awakenings (NNA). However, the sample size was limited and additional studies are required.

According to [49] current wearable devices for sleep analysis should not be used with childrens because physiologically they have higher NNA.

Findings

Emerging technologies for calculating HRV and sympathetic activity have the potential to improve traditional stress detection techniques. Currently, these methods include assessments by a neuropsychologist utilizing stress overload scales (SOS) and the interpretation of polysomnography (PSG) by a neurophysiopathology technician/neurologist, in addition to other expensive blood and instrumental tests. The advantage of these new technologies is their ability to provide continuous measurements over time, which healthcare professionals are unable to do.

ML applied to photoplethysmography analysis using devices has the maximum HRV detection accuracy, achieving 98.28% using the Extra Trees Classifier.

Comparing wearable devices to PSG analysis for computing the number of nocturnal awakenings they have demonstrated superior sensitivity (> 0.91) and adequate specificity (> 0.77). According to the author in [49], however, current wearable devices for sleep analysis should not be used with children due to their higher number of nocturnal movements compared to adults.

In the existing literature, HRV calculation correlates directly with the detected level of stress, whereas analysis of sleep quality (SA) does not. It indicates a statistically significant increase in the likelihood of stress onset. Although the stated accuracy for both HRV calculation and NNA is high, additional clinical testing on adequate samples is required to compare the results with SOS and PSG, to the gold standards.

Despite the need for further research, the benefits associated with these parameters justify their incorporation as routine measurements in hospital and community settings.
Moreover the study [6] recommended that total HRV and vagal measures should be included in allostatic load assessments.
In addition, continuous monitoring of these vital parameters could serve as a useful indicator for determining the efficacy of non-invasive interventions in individuals with stress excess.

6. Limitations of the technology

Reviewed technologies, such as accelerometers, video cameras, smartwatches, and other wearable sensors, all came with some pitfalls. Accelerometers need to be worn and need battery power, cannot store large amounts of data and need some form of wireless connectivity to transfer the data to an intelligent system that historizes it. Usually, patients are reluctant to wear accelerometers for more than a few hours. Computer vision techniques that make use of cameras are truly noninvasive since the user does not have to wear anything, however, they may be subject to some privacy legislation. In fact, the European GDPR prohibits the video recording of faces, analysis, and tracking of citizens without prior signed consent. Instead, smartwatches have the problem of battery life usually not exceeding one week. There might be a problem in being worn even though they are more generally accepted, since they are worn on the wrist, with respect to common accelerometers.
Attempts to classify stress from HRV as well as sleep analysis by means of sensor fusion is still in the early stages. Due to the dynamicity of the wearable market and the introduction of new products at fast pace, scientific validation of newly introduced devices does not keep up with the speed of release of new products on the market. As a result, it is very difficult to provide an accurate estimate of the accuracy of wearable systems for both SO estimation (HRV) and sleep analysis.

7. Further Considerations: the potential of “Mozart Effect” in nursing care plan for stress overload and disturbed sleep pattern in Neurodegenerative Diseases and Mental Health

When stress overload and sleep disturbances are related to emotional stress, innovative techniques such as music therapy can be applied. Although the vibrations of live music can elicit positive reactions, the hectic hospital rhythms cannot accommodate this possibility. In fact, there is often not even the effective time to include the most emotionally redundant music for each patient according to the principles of "reminiscence therapy" [54]; at the same time, such music, if not listened to with personal headphones by the patients themselves, may not be appropriate for everyone, both the patients and the healthcare team, considering that the latter is not only subject to stress overload, but also has a duty to concentrate while working.
In contrast, the music of W. A. Mozart recorded by great performers affects the arousal of brain areas related to attentional processes [55], stimulating meanwhile cerebral areas involved in problem-solving and being open-minded [56],[57]. For the explained reasons it may convey the ideal attitude needed in hospital settings, resulting therefore universally appropriate for both patients and health operators [58]. Nevertheless the methodology adopted to prove the Mozart Effect was respectively based on functional magnetic resonance imaging (Fmri) [55] and on ECG [56],[57].
The first scientific studies of Mozart focused on listening to the sonata k 448 in D major for 2 pianos [56],[57], which was shown to be associated with a significant improvement in psychological stress. Through the autonomic nervous system, music influences the regulation of heart rate, systolic blood pressure, muscle tension, and mydriasis, up to a reduction and stabilization, through the induced musical breathing, of the respiratory rate (RR) [27],[59],[60]. Although it can be assumed how much the respiratory parameters improve in the performing musician, who is in direct contact with the vibrations of the instrument and physiologically involved in the respiratory gymnastics of musical breathing, studies have primarily focused on the effects in non-musicians, proving that these parameters improve even in the passive listener.
The RR is in turn related to HRV, resulting in a significant reduction of psychological stress that is closely

correlated with the levels of neuroinflammation [1]. Listening to music has beneficial effects on a variety of negative stress-induced conditions such as depression and anxiety [57],[60-66].
However, one of the most significant studies of the Mozart effect carried out to date on pediatric participating subjects (45 children with epilepsy) has shown that the choice of Mozart's music is of paramount importance compared to the choice of other control music for its uniqueness in reducing anxiety, leading to a powerful anti-epileptic effect: this was demonstrated by a significant reduction ($p < 0.0005$) in the frequency of epileptic discharges found by electroencephalography (EEG) when subjects listened to Mozart's music compared to control music [61].
Finally, if we consider that the use of sedatives used to treat anxiety, in turn, increases immobility, constipation and could reduce nutrient intake and therefore hypoalbuminemia, worsening the progression and/or increasing the incidence of several illnesses, including pressure ulcers (PU) and neurodegenerative diseases [67], the inclusion of music therapy, which has been shown to be effective not only in reinforcing the "internal rhythm", and motor skills [68],[69] but also in reducing anxiety levels without adverse effects, takes on profound importance.
Mozart's music, as well as flooding the listener with love with its expressive spirituality that culminates in improvisation, has a physical-mathematical architecture with a high index of periodicity [70] that mirrors that of the higher cortical areas: the EEG shows various phenomena, including recall, involved in memory processes, and excitement; among the stimulated areas are those responsible for problem-solving and open-mindedness[56]. This results in an enhancement of the ability of "coping", which is a fundamental resource in stressful situations. At the same time, Mozart's music is full of dynamic signs, progressions, and contrasting themes, and the positive emotional tension not only captures attention and protects against apathy, but always finds a resolution that fulfills the listener's expectations, releasing unforgettable moments of infinite sweetness (and with them the awakening in the listener of the best part of himself, which sometimes, states of illness-inducing deep depression and/or traumatizing/stressful settings, can submerge), and then bounces restarting to sing with passion and admirable commitment. Mozart's music never loses time by wallowing in monotony, viceversa it supports the process of the internal rhythm's formation, coping with critical issues, with positive effects on psychological stress.
Studies on the Mozart effect based on EEG traces have had a sample size of 45 patients as the maximum number of participating subjects (Grylls, E., 2018).
Studies conducted so far on the analysis of other vital parameters such as systolic blood pressure, heart, and respiratory rate, peripheral oxygen saturation have also recruited a small number of participating subjects (Lorch, C. A., 1994).
Nevertheless in literature there are very rare study that measured the effects of quality music on NNA, as presented in [71]. Furthermore, most studies on Mozart focus predominantly on the sonata k 448 in D major for 2 pianos [55],[56],[57], [61], while the effects of an incredible amount of other Mozartian compositions would deserve to be explored.
Thanks to the monitoring of vital parameters including HRV, RR, and NNA the real-time measurement of the Mozart effect could be enriched and enhanced, and could also focus in an easy way on other infinitely sweet compositions by the same author. It would therefore be reasonable to postulate the new frontiers of application of the Mozart effect (or possibly music with similar, albeit simpler, musical patterns and dynamics, as seems to be "Magic moments") on listening to various Mozart compositions recorded through real-time monitoring of vital parameters via wearable and wireless devices, measuring the effects of these not only on heart rate variability but also on sleep quality through NNA, as both are closely associated to stress. Moreover, thanks to the practicality and immediacy of application of the new wearable and wireless devices, monitoring could be carried out on a larger cohort of participants, i.e. in listeners including both patients and caregivers/workers under stress overload, such as health care personnel in traumatizing/stressful environments, without excluding the possibility of self-monitoring by the latter. Among the most useful considerations for an eco-sustainable development, it is of paramount importance to enhance the nursing equipment with technological tools that allow measuring the impact of the Mozart effect on emotional status.This, not only for the negative effects that psychological stress has on, but also because the reduction of emotional tension with non-invasive techniques may allow a progressive reduction in the overall use of specific drugs.

Based on the above considerations and with a view to the routine reproducibility of the music therapy experience, beyond the brief trials conducted using clinical diagnostic instruments as Fmri, ECG, EEG, it would be reasonable to continue future study designs in music therapy adopting confortable wearable and wireless technology and focusing primarily on what is most practical and immediate in the hospital setting, such as music recorded by great performers, i.e. Alfred Brendel, focusing on the uniqueness of Mozart effect.

8. Discussion

The prevalence of wearable technology is on the rise, and the decreasing costs of sensors and devices make it simpler to adopt these technologies. Whether a healthcare institution is public or private, investing in wearable technology can result in a more comprehensive evaluation of patient clinical parameters. It is well known that the emotional and cognitive condition of SO is inversely correlated with HRV. Wearable technologies allow for continuous monitoring of metrics such as the NNA and HRV to provide real-time insight into the patient's stress level. This objective data augments the information provided by stress overload scales, enabling nurses to respond promptly and notify the multidisciplinary team, who can then modify the ongoing therapy accordingly, or deepen the clinical conditions of apparently healthy subjects, increasing the number of diagnoses of SO-related diseases at an early stage, allowing patients maximum response to treatment. On the other hand, as documented by suicides suicides of nurses committed to the covid-19 pandemic, nurses themselves would deserve continuous monitoring of stress levels before, during and after the work shift.

In fact, there are studies that prove that nurses are subjected to certain stressors, and three categories of work-related stress indicators have been identifies:

- Objective company indicators or sentinel events, which are based on events found in the records of hospital companies such as number of absences due to occupational illness and injuries, reduced mental health and depression, and even suicide, unused leave, staff turnover, disciplinary sanctions, etc. [13-14], [72-74].
- Context indicators are represented by roles within the organization, i.e., communication, decision-making autonomy, control, career opportunities (master's degree, master's degree not free or restricted, few/no positions for PhD), possible insufficient economic recognition of the profession's value, role ambiguity, role conflict, pressure-job, intense emotional involvement, mobbing, etc.[74-75]
- Content indicators: work hazards from the work environment and equipment, like unacceptable nurse-to-patient ratios, biohazard stress of infectious disease transmission, rostering (number of night shifts per month and number of rest hours between shifts), matching of skills and job requirements, heavy workload, and physical discomforts, etc. [74], [76-77].

Evidence in the literature also highlights the serious consequences that stress can produce impairing work performance in clinical settings that require very high levels of attention, problem solving and decision skills for prolonged periods of time, compromising the safety of both patients and nurses [7], [78].

Therefore literature leads to the definition of work-related stress as a transversal risk, i.e., incident to both the health of personnel and to the safety of the care provided, as well as the safety of the worker himself.

On the basis of this definition the related regulations, variables worldwide, that force the monitoring of work-related stress in health care, are enacted. As a result of these new legislations, an unmet need arises to provide public and private hospital organizations with an effective work-related stress monitoring system, conducting future trials on nurses and prioritizing the monitoring of areas already identified as at risk on the basis of the aforementioned indicators.

Finally, from a nursing perspective, the equipment of the described devices for monitoring the stress in patients (regardless of whether they are used for calculating stress levels, or for monitoring cardiac and respiratory functions), would make it possible to avoid unnecessary waste of human resources in repeated vital parameters measurements. Conversely, the continuous monitoring of the aforementioned parameters would allow the optimization of nursing resources: considering the serious global problem of the Nursing shortage [79], this last aspect adds a strategic multivalence to the decision of including wearable and wireless wrist devices for clinical monitoring of both patients and healthcare professionals. Finally, the data uploading and archiving processes for each participating subject would require the presence of a research nurse, especially in the initial stages; anyway, the integration of courses and seminars to enhance computer skills is urgently needed for the nursing profession, helping to support the unleashing of Nursing's true potential in the improvement of the Global Health.

9. Conclusions and future remarks

The evaluation of stress levels should be reconsidered and incorporated in the future in order to improve and validate a new planning protocol endorsed by Nanda for non-invasive nursing interventions related to the diagnosis of SO.

Nevertheless, despite the declared excellent accuracy achieved for the calculation of HRV and NNA, a clinical validation of the devices is urgently needed. At present, in fact, the challenge consists in obtaining the necessary funds for the purchase of a large number of smartwatches, to be allocated to a corresponding large dataset of recruited subjects, willing to wear them continuously. Also consider the barriers to compliance with privacy policy regulations, given that individual ECG contains information that could be used to uniquely identify each study participant. Unlike the first accelerometers included in the current review, current nanotechnologies are generally comfortable and increasingly affordable. In the study design of a trial based on a multimodal analysis of the captured signals, it seems logical to choose wearable and wireless devices that incorporate, in addition to the decoding of the signals for the calculation of the HRV, also accelerometers and gyroscopes for the calculation of the sleep analysis. In a desirable multi-centre RTC the use of the same identical multi-sensor model would be indispensable to avoid bias in the analysis of the results. Synthesizing HRV solely from pure photoplethysmography (PPG) data obtained from wearable devices could offer an economical and pratctical approach, but it may be less accurate compared to HRV synthesized from electrocardiography (ECG) guided by RR. However, the accuracy of PPG-based HRV estimation can be improved when combined with machine learning techniques. In this regard, despite the requirement for increased computational power, modern smartwatches equipped with operating systems like Android Wear already possess sufficient computational capabilities to perform machine learning inference. On the other hand, the computation of HRV by means of ECG signal guided by RR requires additional hardware such as ECG sensor as well as Respiratory Inductive Plethysmography or Respiratory Inductive Plethysmography.

By leveraging a large dataset containing multiple signals such as plethysmography, ECG, RR, HRV, and SA analysis (measuring total sleep time and NNA) it is possible to construct an algorithm that takes SA into account, and eventually also SC fluctuations. This would enhance the precision of stress risk estimation and its level by revealing correlations between multiple signals and stress outcomes. Such opportunities are included in the contemporary discipline of Multimodal Deep Learning and AI.

In addition, data derived from continuous monitoring of these vital parameters could serve as a significant indicator for testing and evaluating the efficacy of non-invasive interventions in individuals diagnosed with stress excess.

It is possible to develop an algorithm that takes sleep quality analysis (SA) into account by leveraging a large dataset that includes various signals such as plethysmography, ECG, RR, HRV, and calculations of total sleep time and nocturnal movements. This algorithm would increase the precision of stress risk estimation and determine the level of stress by identifying patterns of correlation between multiple signals and this particular outcome. Such opportunities are included in the contemporary discipline of Multimodal Deep Learning and AI.

Conflict of interest

The authors declare no conflict of interest.

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