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Review

Wearable Solutions for Stress Monitoring for Individuals with Autism Spectrum Disorder (ASD): Systematic Literature Review

Sandra Cano [1,*], Edgar Franco [2], Juan Apablaza [1] and Matías García [1]

1 School of Computer Engineering; Pontificia Universidad Católica de Valparaíso, Chile; {sandra.cano@pucv.cl, juan.apablaza.n@mail.pucv.cl, matias.garcia@pucv.cl}
2 Architecture, Urbanism, and Esthetics Research Group, Faculty of Architecture, Art and Design, University of San Buenaventura, Cali, Colombia; edgar.franco@usbcali.edu.co
* Correspondence: sandra.cano@pucv.cl

Abstract: Research on wearable solutions for individuals with autism spectrum disorder (ASD) has been conducted to detect stress. However, studies on stress detection for an individual with ASD have been limited, especially on how it should design for individuals with ASD. Wearable solutions may be a tool for parents and caregivers for emotional monitoring for individuals with ASD who have a high risk of experiencing very stressful. However, wearable solutions for individuals with ASD may differ from those without ASD. Individuals with ASD have sensory sensitiveness; therefore, they do not tolerate any accessory type or discomfort to use. We used the Scopus, PubMed, WoS, and IEEE-Xplore databases to answer different research questions related to wearable solutions for individuals with ASD, physiological parameters, and algorithms of artificial intelligence used for stress detection studies found from 2013 to 2023. Our review found 34 articles; not all the studies considered individuals with ASD or were out of the scope.

Keywords: wearable technology; autism spectrum disorder; physiological signals

1. Introduction

According to the Diagnostic and Statistical Manual of Mental Disorders (DMS-5) [1], people with ASD have difficulties in communication and social interaction because of atypical information processing and sensory integration abnormalities. These can cause cognitive and emotional overload related to increased stress, which can lead to the appearance of inappropriate social behaviors, especially in individuals with ASD.

Stress in individuals with ASD is thus very common [2]. Prevalence rates can vary between 11% and 84% [3]. Stress can impact the physical and mental health of a person with ASD [4]. People with ASD may be at high risk of experiencing very stressful and traumatic events, which can negatively affect mental health [3]. According to DSM-5, approximately 70% of people with ASD have a comorbid mental health disorder and up to 40% may have two or more. Usually, people with ASD have problems related to sensory processing [5]. Thus, they could experience a sensory overload, in which one or more senses react to stimuli, which can trigger elevated stress levels.

American Psychological Association [6] reports stress classification as acute, acute episodic, or chronic. Acute stress is short-term and associated with the demands of daily activities and events. Acute episodic stress occurs when people experience repetitive stressful challenges and anticipate danger close by, while chronic stress involves ongoing long-term worries that seem to occur permanently. Lazarus and Folkman [7] defined stress and emotion as depending on how an individual values transactions with the environment. So that when people perceive that something important to themselves is out of their control, they tend to feel high levels of stress. Therefore, some people with ASD face stressful situations when they have a variety of social interactions, which can be a problem because these people tend have stress highly amplified [8].

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Stress manifests through physiological responses, which are controlled by the *Autonomic Nervous System (ANS)*. ANS is a part of the nervous system and controls bodily activities, such as digestion, body temperature, blood pressure, and emotional behavior [9]. Therefore, these physiological responses increase when there is a stress stimulus. Studies have used physiological measures to monitor stress in people with ASD [10], such as skin conductivity, heart activity, skin temperature, and brain activity. Therefore, physiological changes associated with negative emotions could help caregivers understand the internal emotional changes in people with ASD.

A review made by Tal-Eldin [11] about wearable devices for monitoring physiological signals to be used for people with ASD. Authors found 25 commercial wearable devices than vary in forms (i.e wristbands, chest strap, vests, garments and shirts, patches, and sleeves), materials, sensors, and parameters, which were designed for people without ASD, but may be adopted by people with ASD. However, some devices are limited in the number of sensors, data reading, data collection and data access and still need to be validated. Most of the reviewed devices are designed for the general population. E4 wristband was designed for autism, which includes photoplethysmography for the heart activity, a 3-axis accelerometer for movements, and an optical, infrared thermometer for detecting skin temperature [12], but to access data is necessary to pay. AutiSense [13] is a wearable technology developed type glove which measures galvanic skin response (GSR), heart rate (HR) and tracks HR variability. However, this device was not validated in individuals with ASD. Another device proposed is a Snap Snap [14] type wristband, which is based in two functions: (1) alerts based on automatic capture of physiological data and (2) tactile interaction (use of bubble wrap, tactile jewelry, etc.), which measures the changes electrical resistance of the body, was made a preliminary test on adults with ASD. Black et al. [15] made a literature review about the use of wearable technology centered on autistic youth. The technology based on accessories and clothes included wrist-worn devices, sensors shirts, and technology worn around the neck. Studies reviewed reported that the device's aesthetics were a concern for participants. Therefore, researchers did not consider aspects such as the size or appearance of the wearable device, which is particularly relevant in ASD, where using socially disruptive devices may further exacerbate social difficulties [16]. Finally, [15,17] indicated few studies related on smart wearables among individuals with ASD. In addition, the use of machine learning (ML) approaches to predict aggressive behaviors have increased [18] using techniques such as Support Vector Machine (SVM), k Nearest Neighbors (kNN), Decision Tree (DT), and deep neural networks.

The growth of technology, meanwhile, has caused a research interest in stress monitoring in people with ASD using biomedical sensors, thereby allowing researchers to capture a person's physiological responses. An emotional state such as stress can be monitored via these physiological responses [19]. Monitoring physiological responses associated with a negative emotional state in a person with ASD can therefore serve as support for caregivers or parents in order to provide information about internal emotional changes and, in turn, allow the individuals themselves to understand in real time the emotional changes they are experiencing - above all, individuals with ASD who have difficulties understanding and recognizing their emotions, making it difficult for them to infer that they are experiencing stress [20]. However, not all individuals with ASD tolerate the same type of wearable. A study conducted by Goodwin et al. [21] where captured physiological signals by a wrist-worn biosensor to predict aggression in individuals with ASD. In the study, 20 youth with ASD were well tolerated using the E4 device. The watchers/wristband and bracelets have been found to be the most preferred wearable technology types [22].

The article is structured as follows. Section 2 defines theorical concepts related to stress and physiological signals for stress monitoring. Section 3 objectives for this systematic review literature which is defined by questions research. Section 4 explains the methodology followed in searching for devices and solutions. Section 5, results found in the articles selected. Section 6 presents a discussion of the reviewed studies. Finally, conclusions.

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2. Background

2.1. Stress

Hans Selye defined stress as : “the non-specific response of the body to any demand” [23]. Stress is associated with several disorders and related health problems. Therefore, in a situation of stress, the body can response to a number of neurohormal changes, which depend on the activation of the hypothalamic-pituitary, neurons, adrenomedullary system, and parasympathetic system. DSM-5 mentions that psychological distress associated with stress and traume is varied and may include anxiety, changes in mood, anger, aggression, or dissociation. Therefore, stress is identified as a risk factor for several other disroders, including depression and anxiety [1]. Individuals with ASD experience multiple stressors, such as bullying, environmental exposures, physical and /or emotional trauma. Therefore, stress can affect learning and motivation [24].

Anxiety and poor stress management in individuals with ASD are prevalent comorbid psychiatric problems[25]. Stress is associate with negative emotions and can be manifested through changes in physiological responses such as electrodermal activity (EDA) [26], heart activity [27], respiration activity[28], and skin temperature (ST) [29]. Therefore, when a person presents stress can have changes in increased heart rate and cardiac output, increased blood pressure, skin sweat glands, and skin neuroendocrine system stimulation [30]. Therefore, the use of physiological signals is the most common and easy-to-access methods for detecting stress [31].

2.2. Physiological Signals

Some physiological responses found for stress detection are cardiac activity, electrodermal activity (EDA), skin temperature, and respiration. Cardiac activity is associated with the heartbeat, so measurements such as heart rate (HR) and heart rate variability (HRV). A sensor based on the photoplethysmography (PPG) technique and widely used in the form of wristbands for measuring heart rate and heart rate variability. The PPG sensor is based on a principle related to blood volume pulse (BVP), which estimates the heart rate and the approximate value of heart rate variability. It is not as accurate as an ECG sensor, however, and the decision to rely on HRV analysis using the PPG technique depends on the parameter it is sought to use [32]. HRV is the variation between two consecutive beats. Therefore a high HRV reflects the fact that an individual can constantly adapt to micro-environmental changes, while a decrease in HRV reflects a high-stress level [33]. HRV and HR are related to emotional reactivity and social skills [34] and can be used to identity stress responses. The device most employed for cardiac activity is blood volumen pulse (BVP), which is measured through a photoplethysmograph (PPG).

EDA can be useful as an indicator of stress [35], also called galvanic skin response (GSR), which measures the conductivity of the skin. GSR is made of a pair of electrodes on the surface of the skin, where one electrode injects an alternating current with a small amplitude into the skin, and the other is used to calculate the impedance of the skin using Ohm's Law, given a certain voltage. GSR is considered as a physiological signal of the activation of the sympathetic nervous system and is considered one of the most sensitive and valid signals of emotional arousal [35].

Skin temperature (ST) [36] is increased when individuals are exposed to emotional events. Respiration is related to cardivascular system activity and is influenced by changes between calm and excited states [37]. ST is easier to measure as it only requires skin contact. However, whether or not it is useful for stress detection depends very much on the location of the measurement. A number of studies indicate that skin temperature increases in the presence of stress [38] and decreases when there is a low level of stress.

Studies reviewed show that real-time detection of stress needs continuous monitoring. Thus, an empowering tool for caregivers can serve to provide information about their internal emotional changes and allow these individuals to understand what they are experiencing in real-time. Therefore, these devices must be portable and non-invasive.

2.3. Wearable Technology for Autism

A systematic literature review was presented by Koumpouros and Kafazis [39], where the authors researched mobile and wearable technologies in ASD interventions. Authors found different flexible sensors that can be integrated into textile fiber, clothes, and elastic bands or directly attached to the human body. In addition, the physiological signals most common integrated in devices wearables were heart rate (HR), electromyogram (EMG), electrocardiogram (ECG), electrodermal activity (EDA), body temperature, arterial oxygen saturation (SpO2), blood pressure (BP), and respiration rate (RR). However, the authors mention that many children with ASD may experience hypersensitivity to clothing and noise, which indicates that it is crucial to consider this when developing solutions integrating wearable devices. In addition, they mention that smartwatches and bracelets are an ideal solution for the population of other devices that can be more obtrusive. However, theses wearables include technological advances such as machine learning (ML), Internet of Things (IoT), cloud computing, and big data.

3. Objectives

The objective of the systematic review is to examine the literature of work that has been carried out on wearable technology to detect stress for people with ASD. The objective is to synthesize current research and increase an understanding of the state of the art of sensors and wearables used on people with ASD and for what purpose. Table 1 shows the list of nomenclature used in this review.

Table 1. List of nomenclature used in this review.

Nomenclature	Referred to	Nomenclature	Referred to
ACC	Accelerometer	LR	Lineal Regression
ANN	Artificial Neural Network	LSTM	Long Short-Term Memory
ANS	Autonomic Nervous System	LF	Low Frequency
BP	Blood Pressure	ML	Machine Learning
BVP	Blood Volume Pulse	MLP	Multilayer Perceptron
CNN	Convolutional Neural Network	NB	Naïve Bayes
DT	Decision Tree	PCA	Principal Component Analysis
DASS	Depression Anxiety Stress Scale	pNN50	Percentage of successive RR intervals that differ by more than 50 ms.
ECG	Electrocardiography	PPG	Photoplethysmography
EDA	Electrodermal Activity	PRV	Pulse Rate Variability
EEG	Electroencephalogram	PSS	Perceived Stress Scale
EMG	Electromyography	PSD	Power Spectrum Density
GSR	Galvanic Skin Response	RBF	Radial Base Function
GB	Gradient Boosting	RR	Respiration Rate
GSM	Gramian Angular Field	RF	Random Forest
HF	High Frequency	RSP	Respiration
HR	Heart Rate	RMSSD	Root mean Square of successive differences between normal heartbeats
HRV	Heart Rate Variability	SC	Skin Conductance

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IBI	Interbeat Interval	SCL	Skin Conductance Level
IMU	Inertial Measurement Unit	SCR	Skin Conductance Response
KNN	K-Nearest Neighbors	SCWT	Stroop Color-Word Test
LDA	Linear Discriminant Analysis	TSST	Trier Social Stress Test

The systematic review aims to address the following research questions:

1- What intelligent wearable solutions are most acceptable for people with ASD?

2- Which physiological signals are used for monitoring stress?

3- Which Artificial Intelligent algorithms have been used to detect stress?

4- What is the process for detecting stress using wearable technology?

4. Methodology

The review was conducted via a systematic search of the published literature available in the last ten years and was carried out according to the guidelines Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [40].

3.1. Selection Keywords

A first search using the search string ("wearable technology" OR "wearable") AND "autism" AND "stress". However, was found few articles related to stress, such as Scopus (36 and 2 no available), IEEEXplore (3), and PubMed(2). Studies found were between 2009 and 2022. However, using these keywords ,the studies found were few, some crucial studies are described.

A study in 2022 by Zwilling et al. [41] assessed the differences in physiological reactions to stressful stimuli between 20 adults without high-functioning ASD. It developed a system able to predict in real-time and inform the caregiver that challenging behavior is about to occur. To develop the prediction model, they compared physiologic parameters, where they monitored during seven days to the participants with ASD, using an intelligent t-shit [42]. In the same year, Willis and Cross [43] researched the potential of Electrodermal Activity (EDA) from wearable devices, where it is used Galvanic Sensor Response (GSR), which can be correlated to stress levels. GSR devices measure tiny changes in sweat secretion when a person exposes an emotionally aouring situation. This study used a device-type wristband. A study made in 2021 by Nguyen et al. [44] examined the effect of a wearable for anxiety detection in 38 participants with ASD ages between 8 and 18 years. Anxiety levels were displayed on three colors: green: calm, yellow: rising anxiety level and red: anxious, where they used a electrocardiogram (ECG) device with electrodes at 256 Hz. In 2020 two studies were found for monitoring stress [30,45]. D'Alvia et al. [45] monitored physiological parameters such as heart rate, breath frequency ,or heart rate variability, where they used a thoracic belt hat embedded goth a sensor for cardiac activity and a sensor for breath monitoring, which fifteen ASD children ages between 2 and 5 years and different levels of disorder were evaluated. Tomczak et al [30] developed an autonomous wearable device type wristwatch to manage data from sensors for individuals with ASD. The device includes sensors for measuring heart rate, skin resistance, temperature, and movement sensors. The device detects stress using an algorithm running time of 20 hours. The algorithm used for stress detection is based on a heuristic rule-based. The device was evaluated with 20 people with ASD, ages between 5 to 24 years. 2019 Masino et al. [46] proposed a machile learning model to detect stress. The classifier models used were logistic regression (LR) and support vector machine (SVM). This study was evaluated with 32 children with ASD, which was designed with two taks to mimic stressful scenarios, where taken a version of the temperament assessment battery [47].

According to results obtained, it was changed the search string by ("wearable technology" OR "wearable") AND "stress", in databases as IEEEXplore, Scopus and PubMed in the last 10 years.

3.2. Inclusion/ Exclusion criteria selection of studies

The inclusion and exclusion criteria were determined prior to conducting the searches. The articles that were included in the review were (1) articles from disciplines related to computer science, stress, and wearable technology; (2) only articles, lectures, and book chapters. Excluded articles were (1) not available in English, (2) literature review or (3) unrelated to the purpose of the study.

5. Results

The initial search of the databases resulted in a total of 8430 articles (3766 Scopus, 902 IEEE Xplore, 1280 PubMed and 2482 Web of Science). Finally, 34 articles published between 2013 and 2023 were selected, considering the inclusion and exclusion criteria. The selected articles allowed us to answer the study questions.

Data Extraction

Data were abstracted following the flow diagram presented in Figure 1, where 34 articles were selected, as described in Table 1.

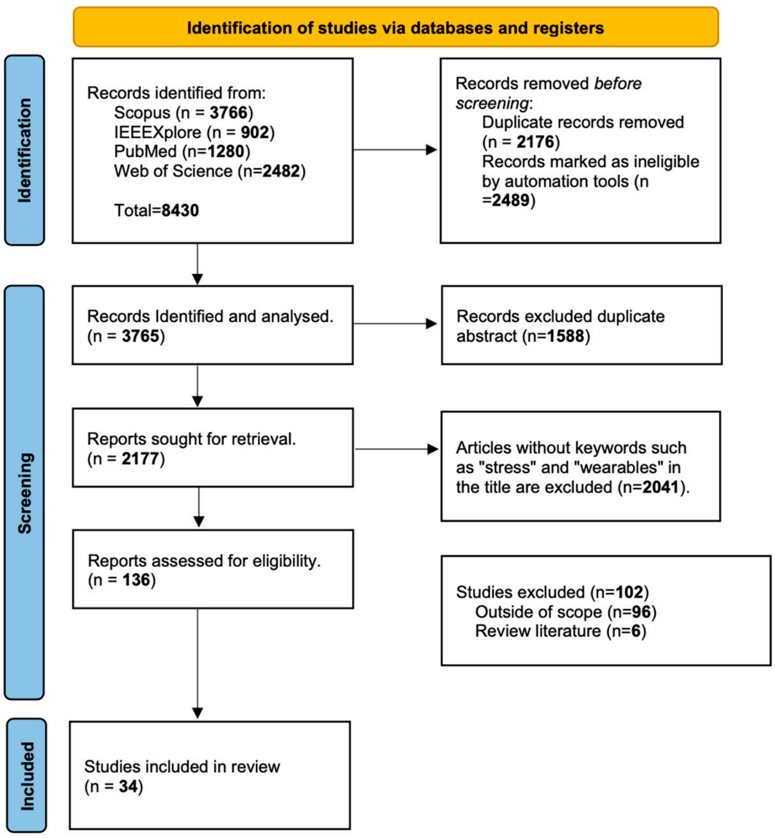

Figure 1. Flow of information of the systematic review process.

The objective of the abstraction was to respond to the following questions:

Question 1. *What intelligent wearable solutions are most acceptable for people with ASD?*

Studies selected found two articles [30,46]. The first study [30] proposed a stress monitoring system for individuals with ASD. The wearable device consists of an autonomous wearable and software that can capture sensor data. The wearable wristband includes sensors such as heart activity, electrodermal activity, skin temperature, and movement. The authors proposed a model for stress detection based on a heuristic rule-based system. The wearable was evaluated with a group of 20

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individuals with ASD (19 males and 1 female), which included 12 children, 6 adolescents and 2 adults. The evaluation was evaluated for the device's acceptance, where three children had adverse reactions to wearing the wristband. The wearable was used for 5 hours with interventions of a therapist.

The second study [46] focused on monitoring stress using two machine learning classifiers such as LR and SVM, where they evaluated it with 22 individuals with ASD, where LR achieved 84% and SM 91% accuracy. The model they proposed was two classes to classify as rest vs stress. Physiological data were taken with a chest strap electrocardiographic sensor. They also designed an evaluation protocol consisting of a first stage of relaxation for 7 minutes, where children viewed a relaxing video. Then, children were engaged in two tasks designed to mimic stressful scenarios. In both studies, physiological signals such as cardiac activity, breathing activity, skin conductivity, and body temperature were used. The parameters used were heart rate (HR), respiration rate (RR), SCL and ST. However, some studies reviewed used the commercial wearable Empatica E4 [48], created initially for children with ASD. For detecting stress in daily life, it is necessary to use a portable device in real-time.

The second study used an instrument called on Temperament Assessment Battery [49], for 5 minutes and viewed a relaxing video design to obtain resting state physiology (InScapes) [50]. It means that induced stress on individuals with ASD to build the dataset.

Table 2 shows a summary of published research on wearable solutions for stress monitoring. Therefore, other studies were focused on individuals without ASD, where used commercial devices such as Polar H7 chest strap and wrist-worn Fitbit Charge 2 [51], E4 by Empatica [52], ADI study watch [53], Apple Watch, Samsung Gear S2 and Polar OH1 [54].

Question 2. *Which physiological signals are used for monitoring the stress?*

Studies reviewed identified heart activity, electrodermal activity (EDA), skin temperature, respiration rate (RR), and movement. Electrocardiogram (ECG) and photoplethysmogram (PPG) are two methods to capture cardiac activity. Electrocardiogram requires two electrodes pads worn on the chest. Some features of ECG are HRV, SDNN, RMSSD, pNN50, VLF, LF, HF, QRS-complex, and P and T waves. The disadvantage is that the stickiness of the ECG electrodes may deteriorate throughout the day, resulting in multiple inaccurate readings [55]. PPG is used to detect the blood-flow change in blood vessels noninvasively. This method uses two sensors to transmit and receive infrared light/radiation. PPG is most used in many stress-found studies (See Table 2) due to its simplicity in attaching the sensors. In addition, PPG can be acquired by a wide range of devices, such as smartphones, tablets, and fitness devices. Some PPG features used in studies found were such as: mean of pulse rates of a time segment, standard deviation of pulse rates of a time segment, variance of pulse rates of a time segment, absolute PSD of LF of PRV, absolute PSD of HF of PRV and absolute PSD of LF/HF of PRV [56]. Other studies have included PPG's time and domain frequency features [57]. PPG also can calculate several essential measures such as heart rate (HR), inter-beat intervals (IBI), hear rate variability (HRV), blood volume pulse (BVP), and heart rate reserve (HRR). HRV is influenced during activities such as exercises, eating and sleep, which is related to emotional arousal and decreases when a person is stressed [54]. A study review [58] showed a list of comparisons using wearable heart monitoring sensors in placement such as chest, finger, and wrist.

EDA, also known as galvanic sensor response (GSR), refers to changes in sweat gland activity which are measured by applying a small electrical current to the skin using two electrodes. A study by [59] showed that a low-resolution EDA signal does not affect stress detection compared to a high-resolution EDA signal. Several studies considered GSR features in the time and frequency domain. EDA has two measures, such as electrical conductivity of the skin (SCL), and skin conductance responses (SCR), changes in shorter periods. SCR indicates the activation of the somatic nervous systems and reflects responses to new events [60]. Some features extracted were the mean of peak amplitudes, median of peak amplitudes, standard deviation of peak amplitudes, root mean square of peak amplitudes, maximum of peak amplitudes, minimum of peak amplitudes, among others [61]. Features of a GSR consist of Latency, Peak, amplitude, Rise time and Recovery time [57]. Typically, GSR requires two electrodes to skin and is usually on the emotionally sensitive locations such as palm, fingers, and feet sole. GSR can be measured in a range from 0.01 µS to 100 µS.

IMU is used to capture accelerometer (ACC) data, which is used as output for stress detection [56] [63]. Normally, the IMU has three sensors such as magnetometer, accelerometer, and gyroscope. Some features used to assess the stress events such as the mean of axis Y, standard deviation of axis Y, variance of axis Y, median of axis Y, sum power spectrum energy of axis Y, Shannon entropy energy of axis Y, and Peak power frequency of axis Y [56]. The accelerometer and gyroscope data can be used to detect the moment of behavioral crises [48].

Some studies have used the ST (Skin Temperature) as an indicator of stress [62][65]. Some studies reviewed have used Empatica E4 watch [52][62]. The ST has shown that under acute stress, the sympathetic nervous system triggers peripheral vasoconstriction, with results in short-term changes in skin temperature. Normally the range is 32 to 35 º C [64]. ST has the potential to provide information about the intensity of the stress response. The temperature sensor in the E4 watch uses an optical, infrared thermometer with a resolution of 0.02º C.

A study presented by [66] has used RR using PPG signals, where the parameter BVP was filtered, and developed an algorithm to estimate the RR. The algorithm was implemented in three steps such as preprocessing, signals analysis, and post-processing. Other studies have used EMG to measure the trapezius muscles in office-like situations [67].

The selection of features is very important because a high number of features with high intercorrelation can lead to an overfitted model [68]. In addition, when there are multi-sensors are recommended, the early fusion of features, usually features, is independently extracted from each modality. In [69] mention that early fusion can promote the unsupervised learning of sensor features.

Figure 1 shows a summary of sensor locations used in studies reviewed. Physiological stress produces an increase in the electrical activity of the sympathetic nervous system (SNS) and produces changes in physiological responses of our body such as cardiac activity, respiration rate, electrodermal activity and skin temperature, which are responses most evaluated in the studies found. However, other responses such as EMG and movement, were used.

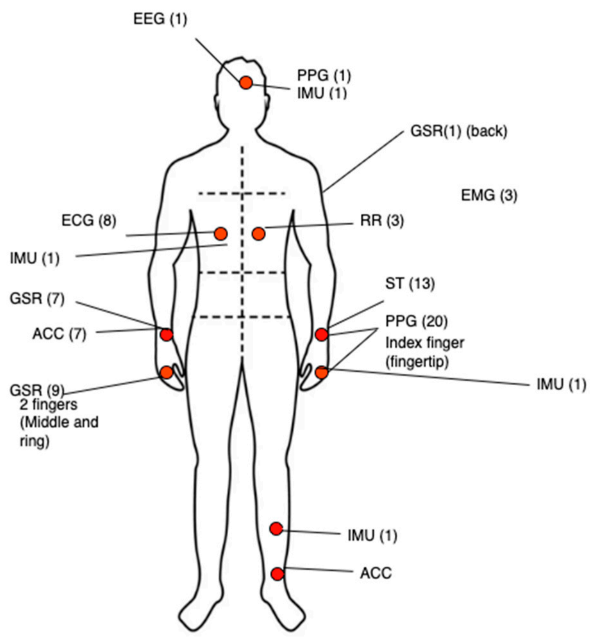

Figure 1. Body locations of physiological sensors in studies reviewed.

Question 3. *Which Artificial Intelligent algorithms have been used to detect stress?*

Many of the studies reviewed developed a classification model of the stress obtaining data from wearable devices or datasets such as RCDAT [70], WESAD [71], PhysioNet [72], AffectiveROAD [73], and SWELL [74]. Several studies reviewed compared different types of classifiers. In [56] was used SVM with three different kernel functions (radial basis, linear and polynomial) obtained the best results with RBF; in [48] used, two machine learning classifier models such as LR and SVM, with two-classes (rest or stress). Both models used a nest leave-one-out cross validation. The best results were obtained with SVM with a 91% accuracy. In [57] used, KNN (K=3), ANNs, Naïve Bayes, and SVM using a Gaussian kernel and RBF. The models were used to detect three classes high stress or stressful, moderate, or normal stress, and relaxing. The best results were MLP and ANN. In [75] present a study for classifying stress considering the WESAD dataset, which contains multi-modal sensor data. This study selected classification algorithms such as LDA, RF, SVM, ANN-2, and ANN-3. The RF classifier had the highest mean and median accuracy among all the algorithms considered, which was 0.94, 0.96, and 0.98. In [66] tested, different machine learning algorithms such as KNN, SVM, MLP, MLP, RF, and GB. The best models for the classification between stressful and not stressful were MLP, RF, and GB. However, in this study, the MLP model was an ideal algorithm for stress detection, where it obtained an 80% sensitivity score. In [59] proposed, a stress detection model where five machine learning algorithms were evaluated, such as SVM, MLP, KNN LR, and RF. The authors obtained the SVM algorithm with balanced accuracy scores with an accuracy score of approximately 90.53% and 93%. In another study [76], used learning techniques such as KNN, LDA, RF, Adaboost, and SVM, where the RF model obtained the best score of 83.34 and 65.73, respectively. This study used two types of classification three-class (neutral, stress, and amusement) and binary (stress and non-stress). Also, in [52], RF obtained the highest prediction accuracy. Another study [77] used DT, NB, RF, and LR, where the DT leave-one-out had better performance in precision (94.40%). Also, they mention that DT and LR easily classify both mental stress and normal conditions using ECG signals. In [58], explore several ML algorithms such as SVM, RF, extraTree, and LigthGBM, where LIgthGBM obtained the best result. In [61] evaluated, the effectiveness of stress detection using machine learning techniques such as LR, SVM, RF, and KNN, where LR obtained the best score of 0.87 and 0.95.

In [78] they were used, deep learning techniques for stress detection, because it requires preforming feature extraction on behavioral measurements and physiological signals and may not be appropriate for the prediction model when working with large amounts of data. Following this approach, [79] used CNN for stress detection, which was formed with three convolutional layers with an activation function set to ReLU (Rectified Linear Activation function). Also, [77] used CNN, obtaining a high classification accuracy of 92.04%. In [80] made, a comparative analysis of the prevalent models employed for stress prediction, such as RF, XGBoost, and DT, where authors described advantages and limitations. This study proposed an architecture for monitoring stress using machine learning techniques as XGBoost, DT, RF, and OSM. The results showed that RF and OSM classifier performed the best score. The stress levels used were normal, high, and low. Also, in [81], RF obtained the best performance with 95.54% and 97.15%, respectively, where RF was evaluated with other ML such as SVM, LDA, KNN, and DT.

Therefore, better results were obtained by ML techniques such as SVM, LR, RF, and CNN.

Question 4. *What is the process for detection stress using wearable technology?*

Studies such as [57,58,61,66,77,78,80,81] follow a supervised learning process that considers a set of stages (see Figure 2) such as data acquisition, data pre-processing, data processing, classification, and evaluation. The data acquisition stage is where data are captured from a wearable technology that can contain one or more physiological sensors. Normally, these data are stored in a database. The data pre-processing stage is used techniques such as filters, normalization, and transformation in the frequency domain. In the data processing stage, the features of each sensor are extracted and merge, as in the study presented by [66], where authors used three techniques (Pearson's Correlation, Recursive Feature Elimination, and Extra Tree Classifier) to estimate the most relevant features. The classification stage is where is selected one or more machine learning classifiers, such as DT, RF, LR, SVM, KNN, MLP, and CNN, which were used in studies found. The evaluation stage, the model is trained and validated with a set of test data. The ML models used in the studies found followed supervise learning of regression and classification, some with 2-class or 3-classs.

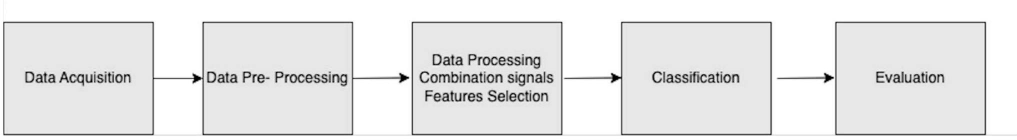

Figure 2. Stages for stress detection.

Studies such as [61,79,82] proposed a neuronal network as CNN or LSTM, as type of deep learning, which can change by layers number and activation function. In [79], the dataset was converted to Gramian Angular Field (GAF) images before training the normalized with the help of a CNN.

Table 2. Summary of published research on wearable solutions for stress monitoring.

Study	Year	Device Type	Signals /Sensors	Parameters/ Features	Communicat ion	Methods	Algorithms	People
[67]	2013	-	ECG, respiration, sking conductance, EMG	HR, SDNN, SCL		Perceived Stress Scale Questionnaire, Visual Analogue Scales (VAS)	-	Subjects between 19 to 53
[56]	2017	Glove	PPG, IMU	STD, variance, PSD, RMS.	Bluetooth		SVM, RBF	-
[46]	2019	Wrist-band	PPG	HR, RR	Bluetooth	Stress tasks	SVM, LR	Subjects with ASD
[83]	2020	-	ECG, Respiration, IMU	HRV, 3-axis accelerometer, 3-axis gyroscope. mean, median, 80th percentile, and quartile deviation	-	-	SVM	Subjects between 24 and 33
[30]	2020	Wrist-band	PPG, ST, GSR		Bluetooth	-	-	Subjects with ASD between 5 and 24
[57]	2020	Wrist-band	PPG, GSR	90 features	Bluetooth		SVR, ANN, ANFIS, kNN, SVM, NB	Subjects between 24 and 27
[63]	2020	Chest band attached to underwear	ECG, EMG, EDA and IMU	-	-	-	-	-
[69]	2020		SC, ST, AC	-	-	Big give Personality.	MLP, LSTM	-
[75]	2020	-	ECG	5 time-domain features	-	-	kNN, LDA, SVM, RF	-
[84]	2020	Wrist-band	PPG	-	Bluetooth	-	ML	Suejects between 25 and 35
[51]	2021	Wrist-band	PPG	HRV	Bluetooth	-	-	Subjects between 19 and 33
[66]	2021	-	ECG	HRV subdivided: 11 features time domain.	-	-	SVM, KNN, GB, RF, MLP	-
[59]	2022	-	EDA, HR	-	-	-	LR, RF, SVM, MLP, KNN	-

[76]	2021	Wrist-band chest-worn	ECG, RSP, EMG, EDA, ST	-	-	-	KNN, AdaBoost, SVM,LDA RF Random Forest, LDA	-
Study	**Year**	**Device type**	**Signals /Sensors**	**Parameters/ Features**	**Communication**	**Methods**	**Algorithms**	**People**
[85]	2021	Wrist-band	GSR, PPG, IMU, ST	-	-	SWS	Baggin-TPMiner	-
[52]	2021	Wrist-band	EDA, PPG, ST		Bluetooth		ANN, k-NN, SVM, RF	
[54]	2021	Wrist-worn, chest strap	PPG, EEG	12 features HRV	Bluetooth	TSST	-	Subjects between 23 and 33
[86]	2021	Wrist-band	ECG /PPG	HRV	SDNN, NN50, pNN50, LF and HF	-	-	-
[62]	2022	Wrist-band	PPG, ACC, ST	BVP, IBI, HRV	Bluetooth	TSST, STAI, Stroop-CW	-	Subjects between 24 and 40
[78]	2021	Wrist-band	EDA,PPG, IMU, ST	-	Bluetooth	TSST, STAI, PSS-10	Deep learning	Subjects between 22 and 30
[87]	2021	Wrist-band	ECG	HRV: FLV, LF, AF, TP		TSST, DASS		Subjects between 20 and 37
[79]	2022	-	RESP, ST, ECG, ACC	-	-	-	CNN	-
[77]	2022	T-Shirt	ECG	HRV,MRR, RMS, TPR,NN50, SDRR	Bluetooth	DASS, SFS, CFS	DT ,NB, RF, LR	Subject between 23 and 35
[65]	2022	-	EEG, ECG, TMP	-	Bluetooth	-	-	-
[58]	2022*	Wrist-band	ECG, EDA, ST, PPG	STD, RR, RMSSD, TINN, FC-max- FC-min, LF/HF	Bluetooth	SCWT, TSST	SVM, RBF	Subjects between 23 and 33
[88]	2022	Writs-band	GSR, ST, ACC		Bluetooth	PSQ	GBT	
[61]	2022		GSR, PPG	Median, SD, amplitude, peaks per minute, mean, RMS	Bluetooth	TSST	DT, k-NN RF, SVM, LR, LSTM	Subject between 67 and 79
[89]	2022	-	EDA, PPG, ST, ACC	-	-	-	SVM, RF, NN	-
[82]	2023	Ear portable	PPG. IMU	-	-	-	CNN	-
[90]	2023	Ring	PPG, GSR	Mean, SDNN, PPI, HRV, SpO2, SCL, SCR, SNS	-	Video	-	Subjects between 23 and 27
[91]	2023	Microsweat	Cortisol	-	-	-	-	-
[53]	2022	Wrist-band	EDA	-	-	-	DASS. DBI	Subjects between18 and 47
Study	**Year**	**Device type**	**Signals /Sensors**	**Parameters/ Features**	**Communication**	**Methods**	**Algorithms**	**People**
[80]	2023	Wrist-band	GSR, PPG, ACC	DSP Algorithm	Bluetooth	-	RF, XGBoost, DT, OSM	
[81]	2023	Wrist-band	GSR, PPG, ACC. ST, ECG, RESP	Mean, mean, SD, Mean RR, amplitude, SCL/SRC min, max	-	-	RF	-

6. Discussion

Individuals with ASD experience high levels of stress, where they have difficulty in communicating distress to family or caregivers. People with ASD can have different physiological response patterns compared with a person without ASD. Jansen et al. [92] showed some evidence of changes in physiological signals such as variability in heart rate arousal in response to public speaking stressors. Therefore, wearable technology has a potential as tool for stress detection in ASD. Monitoring physiological signals may correlate with internal emotional states, such as high levels of stress. According to the circumplex model proposed by Russell [93], an emotion can be understood as a linear combination of two dimensions, such as valence and arousal. Therefore, stress is related to a negative valence and fluctuations in emotional arousal.

Most of the reviewed studies used commercially available wearables. In addition, many of these devices were create for fitness uses. Very few have been created for therapy interventions, such as Empatica wristband [94], which is a portable and wireless device that collects physiological signals such as ST, EDA, PPG, and ACC in real time. However, the acquisition of E4 Empatica is not affordable in terms of cost, as access to the data requires payment. This device can be used to record physiological signals of two ways: (1) real-time, and (2) the user can store the data locally on the device. However, the application does not offer data visualization associated to the stress.

The use of wearable technologies includes design hardware and software. User eXperience (UX) considers the end-user. UX includes the user's emotions, beliefs, preferences, perceptions, physical and psychological responses, behavior, and accomplishment that occur before, during, and after interacting with the product [95]. Studies reviewed do not mention how it should be designed as a wearable solution user-centered with ASD. Therefore, designing a UX for a wearable solution implicates representing the connection between context, user needs and behavior, and content. A tool that explains the various facets of user experience design is the Peter Morville Model [96], where he proposed seven UX factors Usable, useful, desirable, findable, accessible, credible, and valuable. A study conducted by Francés-Morcillo et al. [97] identified design requirements for wearable devices. The requirements are grouped into ten categories such as comfort, safety, durability, usability, reliability, aesthetics, engagement, privacy, functionality, and satisfaction. On the other hand, a study presented by Valencia et al. [98] proposed UX factors for people with ASD such as: (1) engaging, (2) predictable, (3) Structured, (4) Interactive, (5) Generalizable, (6) Customizable, (7) Sense-aware, (8) Attention Retaining, (9) Frustration free.

Therefore, one of the challenges is how to design that the information readily available outside the clinical setting and tolerated by people with ASD and to have regulatory approval. Many devices found are not specifically tailored for unique needs of people with ASD, more than they have sensory sensitiveness, so the device must be user-friendly, and undisturbing when worm during daily activities in the sense of not triggering any discomfort to the user. Only it was found a study [49], where they proposed a wristband made in 3D printing technology. The wearable device evaluated the reactions to wearing the wristband, which obtained results very positive results. However, it does not describe the level of autism of the individuals who were assessed. Umair et al. [54] evaluate the user acceptance of the six most common such as Bitalino, Bodyguard, Polar H10, Polar OH1, Samsung Gear 2, and Empatica E4, commercially wearable for motoring. Authors applied interviews to assess wearability, conform, aesthetics, social acceptance, and long-term use of each device. The device Empatica E4 some participants felt to be heavier and more uncomfortable than other wrist-worn devices because of its electrodes constantly pressing against the skin. However, Empatica E4 has more sensors compared with other devices. A study by Koo et al. [99] mention factors that durability and comfort are more critical to designing wearables. Because it is crucial for long-term monitoring, they also preferred devices made of flexible materials, soft and easy to wear and remove when needed. The authors also mention that when devices are designed for individuals with ASD, the cost of purchasing and gaining continuous service for some devices can be expensive for parents and caregivers.

In a review conducted, studies are limited to wearable device data as an intervention tool for individuals with ASD. To recognize the stress, it is necessarily having training data on physiological

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signals associated with stress crises for individuals with ASD. Therefore, it requires an identity of stress-induced physiological state changes, which may need to be revised. Because when they present, stress is highly amplified. Many studies found the stress detection used machine learning techniques such as SVM, LR, RF, KNN, and CNN, and for training and validation of stress detection models, they use some dataset such as WESAD, PhysioNet, and AffectiveROAD. In addition, the datasets are centered on one type of device, which may affect the detection model if the device is changed. Also, datasets are focused on individuals without ASD. Therefore, one challenge is to assess stress because, usually, to design the model, training data is necessary, but there are no datasets available. In addition, it needs to design a protocol to induce stress to build these datasets, but in autism, it is risk.

7. Conclusions

Studies in wearable solutions for individuals with ASD are limited. Most of the studies that have been reviewed focused on individuals without ASD; only two publications with ASD were found. Wearable technology can provide an alternative for monitoring stress or therapy interventions for parents and caregivers. We also observed that the physiological signals most used in the selected publications are cardiac activity, electrodermal activity, and skin temperature. According to studies reviewed, SCR and HRV are the most studied physiological parameters. Measurement accuracy is a challenge that can significantly affect stress detection. In addition, many of the studies reviewed used accelerometers, showing they can be relevant to stress detection.

Several machine learning techniques are applied for stress detection using commercially available wearable devices or datasets such as WESAD**,** PhysioNet, and AffectiveROAD, where the most used is the WESAD dataset. However, there needs to be more considerable, diverse public datasets.

Few studies were found on how wearable technology can be designed for individuals with ASD. Only a study was found to evaluate the acceptance of the wearable. Therefore, it should be noted that research has yet to discuss UX factors. Most studies evaluated machine learning models but not acceptance or use of the device. In addition, the sensors most used were Empatica E4, Apple Watch, and Polar OH1.

On the other hand, the studies do not mention the problems that can be caused by working with different types of sources, a topic related to data fusion. In addition, an important requirement in the ML techniques followed a supervised approach, which is to have valid labeled data. For stress were found some methods employed for labeling levels of stress such as (1) specific stress/no-stress periods during sessions where user watching images or videos, i.e., induced positive emotions and then applied stress tasks such as SCWT, Stroop-CW, Trier Social Stress Test (TSST), Sing-a-Song Stress Test (SSST) and Visual Analogue Scales; (2) self-reporting via questionnaires such as temperament assessment battery, NASA Task Load Index (NASA-TLX), Depression Anxiety Stress Scale (DASS), Perceived Stress Scale (PSS).

On the other hand, stress levels were evaluated in 2-class (rest and stress) or 3-classess (high, medium, low; neutral, stress, amused) or 4-classess (low, medium-low, medium-high, and high). Finally, one of the limitations in all studies reviewed was the number of subjects and devices available to capture physiological data due to financial, human, and time constraints in academic research groups.

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