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TOPICAL REVIEW

A Systematic Review of Technology-Aided Stress Management Systems: Automatic Measurement, Detection and Control

ALVARO A. JIMÉNEZ-OCAÑA[1,2], ANDRÉS PANTOJA[2], (Member, IEEE), MARIO ANDRÉS VALDERRAMA[1], AND LUIS FELIPE GIRALDO[1,3] (Member, IEEE)

[1]Department of Biomedical Engineering, Universidad de los Andes, Bogotá 111711, Colombia
[2]Department of Electronics, Universidad de Nariño, Pasto 520002, Colombia
[3]Center for Research and Education in Artificial Intelligence, Universidad de los Andes, Bogotá 111711, Colombia

Corresponding author: Luis Felipe Giraldo (lf.giraldo404@uniandes.edu.co)

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ABSTRACT Even though stress response is a defense mechanism of the body to deal with adverse daily situations, prolonged exposure to these effects can trigger significant detriments to physical and mental health. The aim of this systematic review is to identify the use of technological tools in stress management, with a special focus on feedback control systems that include detection, control, and intervention phases. The databases selected for this systematic review, which applies the PRISMA protocol, are Scopus, IEEE Xplore, Web of Science, and Science Direct. We include research works that have experiments involving automated physiological data collection through non-invasive methods and an intervention technique to manage stress. Applying these criteria, a total of 75 articles are included in the final analysis. The quality of the included articles was assessed in the search strategy, the selection process and the data collection process, following the eligibility criteria. Summarizing some results, almost half of the studies included fifty or fewer participants in the experiments and twelve physiological variables were identified, being HR and ECG the most important ones. The most used technique of stress management was breathing and 16 articles used some type of feedback control, mainly biofeedback. Several promising physiological variables and intervention techniques are identified for implementing stress management systems. Although using machine learning in stress detection is common, its application to develop feedback control systems is limited. Moreover, it was found that the theory of control in dynamical systems has not been applied yet to design automatic stress management systems.

INDEX TERMS Automatic measurement, feedback systems, intervention techniques, physiological signals, stress management, systematic review.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Stress is a common cause of mental and physical disorders, and its study is a research topic of growing interest. Emerging technologies to measure and process physiological signals, the generation of a variety of virtual environments, and the definition of intelligent decision-making strategies have opened new paths to approach stress management. The motivation to develop this review is to know the current state of the art in this important topic and to identify current research needs and opportunities.

Stress has been defined as the state experienced when there is a real or perceived risk of homeostasis failure [1]. In addition, the homeostatic balance can be reached through adaptive responses. Another definition of stress from a different approach proposes that stress is a failure to control a fitness-critical variable in a biological control system [2].

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Ursin and Eriksen [3] expanded this concept using a cognitive activation theory, which defines four aspects of stress: stress stimuli, stress experience, stress response, and feedback from stress response. The first aspect is focused on the event that activates the response, usually called stressor, which could be sensed as positive or negative depending on the individual. The second aspect refers to the subjective appraisal of stimuli, which is considered as stress when stimuli are negative or threatening. On the third aspect, the authors state that there is a general response to stimuli, characterized by a raise of arousal. This increase in arousal is defined as activation. In the last aspect, it is assumed that the stress response is capable to modify the stressor, which produces some expectancies of response outcome. Thus, the authors claim that when expectancies are not accomplished because what is expected is different from what occurs, there is a general and unspecific stress response alarm.

The intensity and chronicity of stressors influence the stress response [1]. Typically, this response includes innately reactions from the central nervous system and peripheral organs, such as the facilitation/inhibition of neural pathways for adaptive/nonadaptive functions, or increased oxygenation and nutrition of the brain, heart and skeletal muscles. Due to these changes, acute-stress response can cause disorders such as asthma, urticaria, migraines, abdominal, pelvic and lumbar pain, indigestion, diarrhea, and panic attacks. In addition, repeated conditions of acute stress without effective responses produce chronicle stress that can cause more serious problems, such as hypertension, diabetes, depression, anxiety, cognitive dysfunction, and insomnia. Therefore, Achicanoy et al. [4] suggest that some of these psychological disorders lead to self-destructive behaviors that are difficult to treat.

To maintain the homeostasis condition and reduce the impact of stress response in the individual, some research studies have been focused on techniques of coping, emotion regulation, self-regulation, and stress management. Some of the most used techniques include cognitive behavioral therapy, autogenic training, breathing exercises, relaxation techniques, guided imagery, mindfulness, yoga, Tai-Chi, and biofeedback [5]. Currently, many of them are supported by technology. For instance, biofeedback is a procedure in which subjects are fed back with their own physiological measurements, usually using a visual-based interface. These measurements usually come from cardiac, electrodermal, muscle, and brain activities [6]. The aim of biofeedback is to provide a strategy of physiological activity modification, using feedback information and one's own stress-management skills to improve the individual's well-being [6].

In general, in stress management, physiological data are collected to know the subject's current state, and, based on these measurements, decisions are made according to a set of policies that are designed to reduce the impact of the stress response on the individual. Interestingly, from a control-theory perspective, this is clearly a closed-loop control system. A feedback control system is composed of a plant, which is a dynamical object to be controlled; the output that corresponds to the measured variable of interest; and a controller, a decision-making strategy that tries to direct the output of the plant to a desired state [7].

Although there are reviews on stress-detection systems [8] and on the impact of biofeedback techniques in stress management [9], [10], the aim of this work is to review those papers that report the development of technology-based management systems for detection and intervention of stress. It is our particular interest to analyze such studies considering the definitions given by the control theory of dynamical systems and identify research needs and opportunities.

B. REVIEW OBJECTIVES

According to above motivation, the research questions to be answered through this systematic review are:

- In stress management systems, what are the most used technological tools in detection and intervention?.
- What are the main control strategies that have been used in stress management systems?.
- Are there studies that apply automatic control to stress management?.

Thus, we define the following review objectives:

- Examine the state of art in the application of physiological signals and intervention techniques in experiments aimed to stress reduction.
- Describe the usage of technological tools in the phases of acquisition, processing, and intervention of stress management systems, considering the definition of control in dynamical systems.
- Identify opportunities and needs to develop further research in the field of stress management from an engineering approach.

II. METHODS

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [11] to do our analysis. Based on this systematic review protocol, next sections explain how the process was performed.

A. ELIGIBILITY CRITERIA

According to the research questions, we discarded works focused on other psychological disorders, emotions, consequences of stress on health, and causes of stress. Also, articles must include an experimental component, resulting in the exclusion of theoretical research and reviews.

Although physiological measures can include hormones (e.g., cortisol and catecholamine), enzymes (e.g., alpha amylase), or proteins (e.g., immunoglobulin A), we decided to discard them because our interest is on automated non-invasive methods. In consequence, only articles with experiments that measured physiological signals automatically through electronic devices are included.

Regarding the participants in the experiments, adult population of any age, gender, occupation, or social status are included. However, articles about people with chronic physical or mental diseases, such as diabetes, hypertension, cardiac illnesses, or depression are excluded. Research focusing on very specific condition groups, for example war veterans, autistic people or cancer survivors, are also excluded.

As a final eligibility criterion, we included articles which have had at least one clear technique for reducing or managing stress, whatever it might be, excepting pharmacological treatment. Consequently, research works focused only on stress detection are excluded.

Regarding report characteristics, we decided to include English articles published in journals without date restriction.

B. INFORMATION SOURCES

To conduct the search, we looked for available databases in the electronic resources of the Universidad de los Andes. As a result, we chose four electronic databases: Scopus, IEEE Xplore, Web of Science, and Science Direct. The first two ones were consulted on February 25th 2022, and the rest of them were consulted on February 26th 2022. After, we updated the database search on November 4th 2022.

C. SEARCH STRATEGY

For Scopus, we limited language to English, publication stage to final, source type to journal, and document type to article. After multiple tries using different keywords to improve the results, the search equation applied to title and abstract fields in the option advanced search was: [(''stress reduction'' OR ''stress control'' OR ''stress management'') AND (physiolog* OR loop OR feedback OR ''machine learning'')].

For IEEE Xplore, we applied the filter of journals only, and the other limits were applied later over the exported file. In the advanced search, the search equation used for all metadata was: [(''All Metadata'':''stress reduction'' OR ''All Metadata'':''stress control'' OR ''All Metadata'':''stress management'') AND (''All Metadata'':physiolog* OR ''All Metadata'':loop OR ''All Metadata'':feedback OR ''All Metadata'':''machine learning'')].

For Science Direct, the filter research article was applied in the field article type. As in the other cases, using the advanced search option, in the title, abstract and keywords fields, the search equation applied was: [(''stress reduction'' OR ''stress control'' OR ''stress management'') AND (physiological OR loop OR feedback OR ''machine learning'')].

Finally, for Web of Science, the same search equation was applied, for the same fields and including filters for language and document type, English and articles, respectively.

D. SELECTION PROCESS

All researchers (AAJ, AP, LFG) were responsible for defining the inclusion criteria and the selection of keywords used in the searches of databases. One researcher (AAJ) run the search process and consolidated the results in a common spreadsheet. Duplicated entries were discarded. Afterward, title and abstract screening was applied and articles with obvious exclusion criteria were removed. For articles whose exclusion criteria were not clear enough, the researchers (AAJ, AP, LFG) achieved a consensus decision. To develop full text screening, reports were retrieved by one researcher (AAJ), and important information was extracted to consolidate an analysis matrix. Next, eligibility articles were classified by one researcher (AAJ) based on criteria fulfilment and using the matrix information. Finally, all reviewers (AAJ, AP, LFG) analyzed this classification result, choosing the resultant articles to be included in this review.

E. DATA COLLECTION PROCESS

To collect relevant information from the articles, we implemented an analysis matrix in an Excel® spreadsheet. This matrix was divided in four sections and data were collected by one reviewer (AAJ).

- **Experiment.** This section included the fields: number of participants and age range; experiment duration; group characteristics; and country where the experiment was run.
- **Acquisition.** In this section, we considered: physiological measures used; instrument or equipment; frequency of physiological measures; processing procedures; psychological measures; and frequency of psychological measures.
- **Stressor.** Tool used to produce stress during the experiment, if applied.
- **Stress management.** The fields included in this section were: used intervention technique; brief explanation of the applied method; and modified parameters in closed-loop.

F. RISK OF BIAS ASSESSMENT

This article is focused on the description and compilation of methods and technological tools used in the state of the art of stress management systems with diversity of experimental protocols, physiological signals, intervention techniques, technological tools, and types of control used. Similarly to [12] and [13], we did not conduct a formal risk of bias assessment of each study included in this review. To ensure the high quality of the studies, we defined rigorous restrictions in the search strategy section, such as document type, source type, and publication stage. In addition, we carefully defined and applied the aforementioned eligibility criteria, so that only studies that strictly met them were included in this review.

III. RESULTS

A. STUDY SELECTION

As it is shown in Fig. 1, a total of 2386 records were obtained from the search in all databases. These records were organized in a unique spreadsheet, after which 817 duplicated records were eliminated using the tool ''remove duplicates'' of Excel®. However, within the databases, some titles of identical articles differed in a few words, symbols, or capital

TABLE 1. Number of citations.

Range of citations	References	No. of articles	%
0	[16]–[24]	9	12.0
1-25	[5], [15], [25]–[72]	50	66.7
26-50	[73]–[78]	6	8.0
51-75	[79]–[81]	3	4.0
76-100	[82]	1	1.3
101-125	[83]–[85]	3	4.0
126-150		0	0.0
151-175	[86], [87]	2	2.7
176-200	[88]	1	1.3

and lower letters. We identified them by inspection, and 108 additional records were also removed.

Applying the eligibility criteria in title and abstract screening, 143 records were obtained. From these records, 120 were retrieved through the institutional access in the databases, and Google academic search engine. Afterward, full text screening was applied following three strict compliance criteria: information about number of experiment participants; existence of automated physiological measures; and existence of at least one stress management technique. As a result, a total of 75 articles were included in this systematic review. Although [14] complied with the eligibility criteria, this study was excluded because it is a continuation of [15] and contains the same information analyzed in this review.

B. STUDY CHARACTERISTICS

To present the characteristics of the included studies, we used the databases information and the analysis of the matrix extracted from the full text review. We organized the results in groups to facilitate further discussion.

1) ARTICLE CHARACTERISTICS

Fig. 2 shows the year of publication of the articles included in this review. Although stress management is a field that has been studied long time ago, experiments with automated physiological measures and intervention techniques in healthy people without specific conditions seem to rise gradually since 2006. However, it is possible to identify a decrease at the last two years.

Another important characteristic usually analyzed is the number of citations. As presented in Table 1, 12.0% of articles have not been cited yet. In contrast, around 21% of papers have been cited more than 25 times and 66.7% of the papers has between 1 and 25 citations.

2) SIGNAL ACQUISITION AND PROCESSING DETAILS

Reviewed papers can also be classified according to the detailed information about the acquisition instruments, and pre-processing and analysis of the physiological signals. Table 2 summarizes if the articles provide information about the mentioned technical topics.

In the table, the first columns describe information about the acquisition instrument. Column ''Type'' indicates whether the instrument was a sensor or a commercial device. If the column ''Characteristics'' is checked, the paper provides technical data about the instrument, such as sampling rate, resolution, calibration or other electrical characteristics. The column ''Reference'' indicates the model and manufacturer of the instruments when applicable. In most cases, technical characteristics are not provided since datasheets of commercial devices are available. Regarding the signals, the ''Pre-processing'' column is checked when the article specifies methods to remove artifacts, apply filters, and/or normalize physiological data. Moreover, the ''Feature extraction'' column is ticked when the article specifies the variables extracted from the signals (e.g., time or frequency domain indexes), like some of the ones described in the next section. Finally, the ''Processing'' column presents how the data were processed and analyzed. In most of the articles, statistical analysis is applied to look for patterns and trends in the data in order to establish causal relationships between variables.

Different statistical methods has been used to analyze the results, such as ANOVA, MANOVA, Mixed ANOVA, ANCOVA, Pair T-Test, Post hoc, Multilevel Modeling, or General Linear Models. In this regard, each article assesses multiple results depending on the physiological signals, extracted features, and the number of experimental groups and phases of the studies. Therefore, the outcomes are evaluated according to specific conditions in each work to conclude about results. Unsurprisingly, in most cases there are no simple and definitive conclusions, and consequently, we have not included a concept about the success of the evaluated techniques.

3) EXPERIMENT CHARACTERISTICS

The number of participants in the experiment is presented in Table 3. 52.0% of the studies included between 1 and 50 individuals; 72.0% recruited 75 or less individuals; and only 16.0% included more than 100 participants. The only research work that included more than 200 participants, 5526 exactly, did not run an experiment. Instead, it took data from archival information of a relaxation center. Information about age was available for 57 of 75 articles. According to these articles, all participants were adults aged 18 or older, and the mean age was 30.5 years.

Although one of the eligibility criteria to screen the articles was the automated physiological measures, it is also important to analyze the usage of psychological measures during the experiment. As indicated in Fig. 3, 96.0% applied at least one psychological test, such as Perceived Stress Scale (PSS), State Trait Anxiety Inventory (STAI), Visual Analogue Scale (VAS), Beck Depression Inventory-II (BDI-II), Numeric Rating Scale (NRS), Positive Affect and Negative Affect Schedule (PANAS), the 16-item Penn

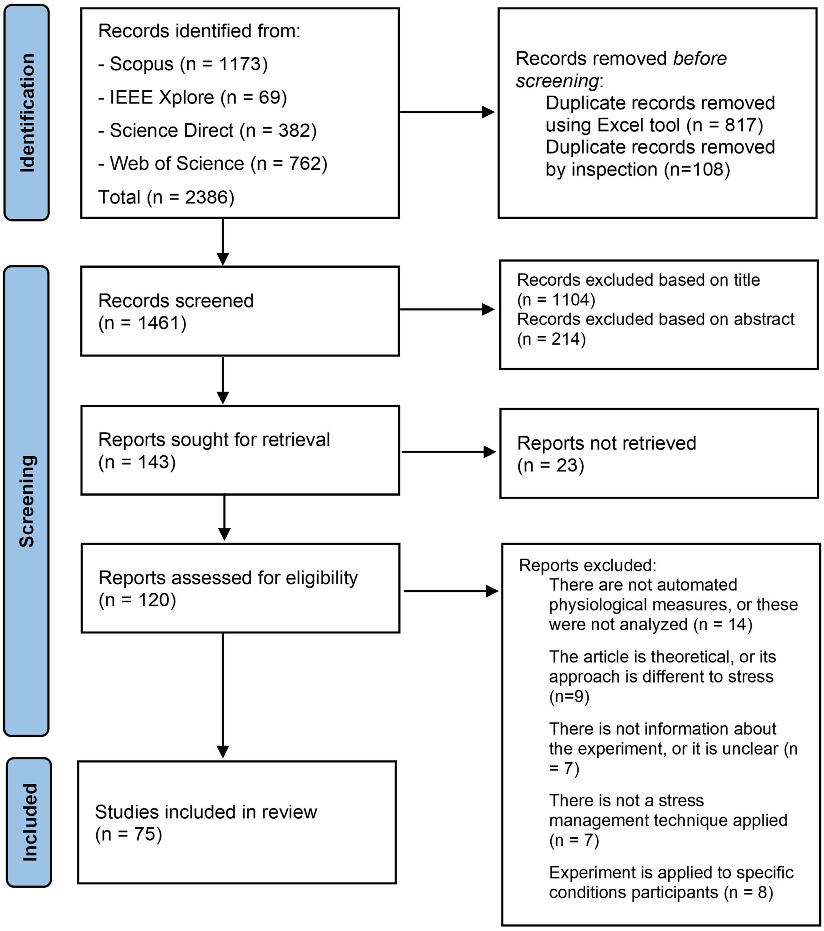

FIGURE 1. PRISMA flow diagram. This diagram summarizes the systematic process of screening records to select the articles included in the review.

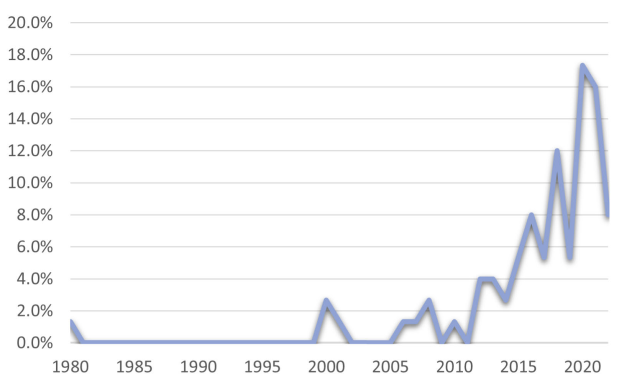

FIGURE 2. Year of publication of articles included. The articles included in the review were published from 1980 to 2022.

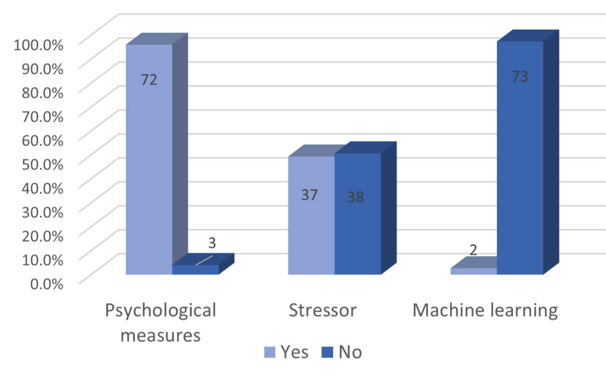

FIGURE 3. Experiment characteristics. Bars display the application of psychological measures (left), stressors (middle), and machine learning techniques (right) in the experiments.

State Worry Questionnaire (PSWQ), Profile of Mood States (POMS), Nine-item Psychological Stress Measure (PSM-9), the Student-Life Stress Inventory (SLSI), the Depression, Anxiety, and Stress Scale (DASS), Chronic Stress and Burnout Scale (CSBS), or Dundee Stress State Questionnaire (DSSQ).

An important aspect of the methodology used to conduct the experiments is the stressor used. In this review, as Fig. 3 shows, 49.3% of articles included a stressor. Some of stressors used are Stroop test, the Trier Social Stress Test

TABLE 2. Signal acquisition and processing details provided in the articles. In the processing column, S refers to statistical analysis and ML to machine learning.

Article	Acquisition instrument			Pre-processing	Feature extraction	Processing
	Type	Characteristics	Reference			
[5]	Device		Empatica E4 smart band and CE(0123)- Harvard Medical Devices	x	x	S , ML
[15]	Device	x	Porti7 bioamplifier - TMSI	x	x	S
[16]	Device	x	MindBand EEG headsets - NeuroSky ThinkGear		x	S
[17]	Device	x	Biopac BioNomadix1	x	x	S
[18]	Device	x	Emotiv Epoc+	x	x	Unspecified
[19]	Device		NIRSport 2 - NIRx Medical Technologies LLC		x	S
[20]	Device	x	MindBand EEG headsets - NeuroSky ThinkGear		x	S
[21]	Device	x	Emotiv EPOC EEG headset - ErgoLAB	x	x	S
[22]	Device		Activtracer AC-301A - GMS and TRS-20 system - Hamamatsu Photonics K.K.		x	S
[23]	Device		myBeat - Union Tool Co.		x	S
[24]	Device		Standard 19-electrode array		x	S
[25]	Device		Omron BP742N 5 series			S
[26]	Device		Autogen 30 Myograph	x		S
[27]	Device		BioGraph-Pro-Com+ system - Thought Technology			S
[28]	Device		Zephyr BioModule Device (version 3.0)	x	x	S
[29]	Device	x	Shimmer ECG Unit and Shimmer3 GSR+	x	x	S , ML
[30]	Sensor				x	S
[31]	Device		Actiheart device - CamNtech		x	S
[32]	Device		Equivital Life Monitor Belt	x	x	S
[33]	Device		Automated sphygmomanometer cuff			S
[34]	Device		ProComp Infiniti - Thought Technology		x	S
[35]	Device	x	ekgMove - Movisens	x	x	S
[36]	Device		Blood Pressure Monitor			S
[37]	Device and sensor	x	Muse EEG headband - InteraXon and electrodes for GSR			S
[38]	Device	x	Power Lab 4/30 - ADInstruments	x	x	S
[39]	Device		Biopac system			S
[40]	Device		Rossmax XI Blood Pressure Monitor			S
[41]	Device		Boso medilife S			S
[42]	Device	x	Power lab 2/20 - ADInstruments	x	x	S
[43]	Device	x	TMSi 16 channel porti-system and MobiMini portable device- Twente Medical Systems international	x	x	S
[44]	Device	x	PowerLab 16/30 - AD Instruments 2009	x	x	S
[45]	Device	x	Cardiovascular belt - Pisa National Centre of research		x	S
[46]	Device		emWave Pro®	x		S
[47]						S
[48]	Device		Biopac MP150 and BioNomadix	x		S
[49]						S
[50]	Device		GE Dinamap® PRO 400 Vitals monitor			S
[51]	Device		Schuhfried Physiorecorder GmbH A-2340			S
[52]	Device		V-Amp system, Brain Products GmbH, Gilching and Biofeedback2000xpert system, Schuhfried GmbH	x	x	S

TABLE 2. *(Continued.)* **Signal acquisition and processing details provided in the articles. In the processing column, S refers to statistical analysis and ML to machine learning.**

[53]	Device		POLAR H10	x		S
[54]	Device		Omron 10 Series			S
[55]	Device		Biopac EDA100C			S
[56]	Device		Ubiomacpa - Biosence Creative and BIOS-ST BioBrain		x	S
[57]	Device	x	VITAPORT–II TEMEC Instruments B.V.		x	S
[58]	Device	x	Biopac MP150 and Bionomadix	x		S
[59]	Device		Omron 3			S
[60]	Device	x	Omron BP785			S
[61]	Device		Calibrated digital oscillometric sphygmomanometer - Tensoval			S
[62]	Device		PowerLab 26T - AD Instruments		x	S
[63]	Device	x	Biopac ECG100C	x	x	S
[64]	Device		Omron HEM-780			S
[65]	Device		SA-3000P - Medicore Co.		x	S
[66]	Sensor		emWave		x	S
[67]	Device		BioGraph Infiniti Procomp			S
[68]	Sensor	x	Pulse sensor Amped			S
[69]	Device		Firstbeat Bodyguard II	x	x	S
[70]	Device		Biopac MP-150			S
[71]	Device	x	Bionex - MindWare Technologies	x	x	S
[72]	Device		Fitbit wristbands			S
[73]	Device		Omron HEM-705CP			S
[74]	Device	x	Biofeedback2000xpert system - Schuhfried GmbH	x	x	S
[75]	Device	x	I-330 C-2 interface - J &J Engineering		x	S
[76]	Device		Polar Vantage XL			S
[77]	Device		Vita Stat, model 900-5			S
[78]	Device	x	Bioharness - Zephyr	x	x	S
[79]	Device		Omron EVOLV and EcgMove3, EdaMove3 - Movisens		x	S
[80]	Device		Criticon Corporation automated blood pressure monitor			S
[81]						S
[82]	Device		Vernier LabQuest® Mini	x		S
[83]	Device	x	Dinamap 845 and J &J I-330 system (M-501 and T-601 modules)			S
[84]	Device	x	PORTAPRES		x	S
[85]	Device		HEM-1020, Omron			S
[86]	Device		DS-140 - A &D Company			S
[87]	Device		eMotion monitor	x	x	S
[88]	Device	x	Omron M4-I			S

(TSST), the Mirror Tracing Task (MTT), the Wechsler Adult Intelligence Scale (WAIS), memory task, arithmetic task, Paced Auditory Serial Addition Task (PASAT), discomfort induced by virtual reality experiences, sequence of heavy metal song, and video games.

Application of machine learning methods was also analyzed in this review. Only 2 articles [5], [29], which represent 2.7% from total, reported the application of these kind of techniques, as indicated in Fig. 3. In [29], the researchers used features extracted from electrocardiogram and electrodermal

TABLE 3. Number of experiment participants.

Range of participants	References	No. of articles	%
1-25	[5], [28], [29], [31], [39]–[41], [43], [47], [52], [60], [62], [66], [72], [78], [81], [83], [85], [88]	19	25.3
26-50	[18], [19], [21]–[23], [26], [27], [32], [33], [37], [50], [53], [59], [65], [68], [73], [75], [77], [86], [87]	20	26.7
51-75	[15], [17], [34], [42], [46], [49], [51], [55], [56], [63], [67], [71], [74], [80], [82]	15	20.0
76-100	[16], [30], [36], [54], [58], [61], [64], [79], [84]	9	12.0
101-125	[20], [24], [38], [48], [69], [70]	6	8.0
126-150	[35], [44], [45], [76]	4	5.3
151-175		0	0.0
176-200	[57]	1	1.3
>200	[25]	1	1.3

activity as inputs, and defined labels based on self-reports, resulting in a model to predict the effects of the relaxation protocol. Similarly, the same physiological signals were used to detect stress levels in [5]. For the classification stage, techniques as multilayer perceptron (MLP), random forest (RF), K-nearest neighbor (kNN), linear discriminant analysis (LDA), and support vector machines (SVM) were applied to obtain an classification model. Moreover, a dimensionality reduction stage was implemented using techniques such as correlation-based feature selection (CBFS) and principal component analysis (PCA).

4) PHYSIOLOGICAL MEASURES

As a result of the analysis of the articles included, we identified that the physiological measures are heart rate (HR), electrocardiogram (ECG), blood pressure (BP), electrodermal activity (EDA), breathing rate (BR), electroencephalogram (EEG), photoplethysmogram (PPG), electromyogram (EMG), skin temperature (ST), impedance cardiogram (ICG), oxygenated hemoglobin (oxy-Hb), and pupil diameter (PD).

The frequency of automated physiological measures used in the experiments are presented in Fig. 4, where about 39% of studies apply HR measurement, while ECG and BP are used in 36.0% and 30.7% of experiments, respectively. In fact, if we analyze the cardiac activity using HR, ECG and PPG, this kind of measurements is used in 63 articles from the total of 75 (i.e., 84% of the papers). Furthermore, all experiments with ECG and PPG measures calculate heart rate variability (HRV) to use it as the final variable of analysis. Other measurements frequently used in the included research are EDA (22.7%), BR (16%), and EEG (14.7%).

Often, research works include more than one measure in each experiment, as indicated in Table 4. As the table shows, 36.0% use only one measurement, where ECG and HR are most frequently chosen in 14.7% and 8.0% of the papers, respectively. In contrast, 64.0% of the articles combined at least two different physiological measures. With 22.7%, most

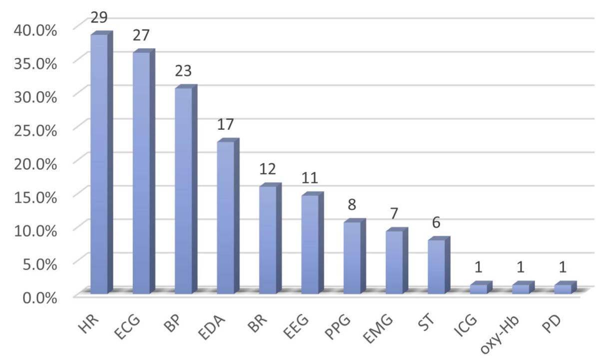

FIGURE 4. Physiological measures used. Frequency of use of heart rate (HR), electrocardiogram (ECG), blood pressure (BP), electrodermal activity (EDA), breathing rate (BR), electroencephalogram (EEG), photoplethysmogram (PPG), electromyogram (EMG), skin temperature (ST), impedance cardiogram (ICG), oxygenated hemoglobin (oxy-Hb), and pupil diameter (PD).

applied combination is BP and HR, followed by far by ECG and BR (5.3%); ECG and EDA (4.0%); PPG and EEG (4.0%). All other combinations have a low frequency of use, less than 2.7%.

Typical procedures for signal processing are used in most articles, such as filters, artifact removal, transformation to frequency domain, and feature extraction. As mentioned above, HRV was calculated from ECG and PPG measures in all articles that used these signals. In these cases, processing focused on different indexes of HRV, mainly, standard deviation of NN intervals (SDNN), root mean square of successive RR interval differences (RMSSD), and low to high frequency ratio (LF/HF ratio).

5) STRESS MANAGEMENT TECHNIQUES

Several experiments used more than one technique of stress management. Some of them present complementary techniques, and some others have reference techniques to

TABLE 4. Combination of physiological measures used.

No. of signals	Physiological measures	References	No. of articles	%
1	BP	[47]	1	1.3
	HR	[46], [49], [68], [72], [76], [80]	6	8.0
	ECG	[17], [23], [31], [35], [42], [44], [57], [63], [69], [82], [87]	11	14.7
	PPG	[65], [66]	2	2.7
	EDA	[55], [70]	2	2.7
	EEG	[16], [20], [24]	3	4.0
	BR	[32], [51]	2	2.7
2	BP, HR	[25], [33], [36], [40], [41], [50], [54], [59]–[61], [64], [73], [77], [81], [85], [86], [88]	17	22.7
	BP, ECG	[84]	1	1.3
	HR, EDA	[37]	1	1.3
	ECG, EDA	[29], [38], [48]	3	4.0
	ECG, EEG	[30], [43]	2	2.7
	ECG, BR	[28], [45], [75], [78]	4	5.3
	ECG, ICG	[71]	1	1.3
	ECG, oxy-Hb	[22]	1	1.3
	PPG, EEG	[52], [56], [74]	3	4.0
	EMG, ST	[26]	1	1.3
	EDA, EEG	[18]	1	1.3
3	BP, ECG, EDA	[79]	1	1.3
	BP, ST, EDA	[5]	1	1.3
	HR, EMG, EDA	[53]	1	1.3
	HR, EDA, BR	[39]	1	1.3
	ECG, PPG, BR	[15]	1	1.3
	ECG, EMG, EDA	[58]	1	1.3
	ECG, ST, EEG	[62]	1	1.3
	PPG, EDA, EEG	[21]	1	1.3
4	BP, EMG, ST, EDA	[83]	1	1.3
	HR, EMG, ST, BR	[27]	1	1.3
	HR, EMG, EDA, BR	[67]	1	1.3
	PPG, EDA, BR, PD	[19]	1	1.3
6	BP, HR, EMG, ST, EDA, BR	[34]	1	1.3

compare results. We categorized the most used interventions as follows: breathing, mindfulness, mindfulness-based stress reduction (MBSR), cognitive behavioral therapy (CBT), yoga, meditation, tai chi, coaching, progressive muscle relaxation (PMR), positive psychology, scent therapy, music, sounds, green space, built space, biophilic design, and dog therapy.

Fig. 5 presents the frequency of use of these intervention techniques. According to this figure, the most used technique is breathing therapy with 24.0% of the papers, while green space is applied around 19%, and music and mindfulness in 12.0%. Techniques such as MBSR and meditation have a 10.7% of use. The frequency of use of the other techniques is under 10%.

Some techniques are not included in the above figure because they were used in only one paper (1.3%). These methods include social support stress management (SSSM), massage chair, chi machine, rejuvenation lounger, physical education program, reiki touch, traditional thai massage, acupressure, relaxation, chinese calligraphic, art, and work-life balance (WLB).

During the intervention stage, we identified the usage of novel technology such as: virtual reality in 10 of 75 experiments, which corresponds to 13.3% [20], [32],

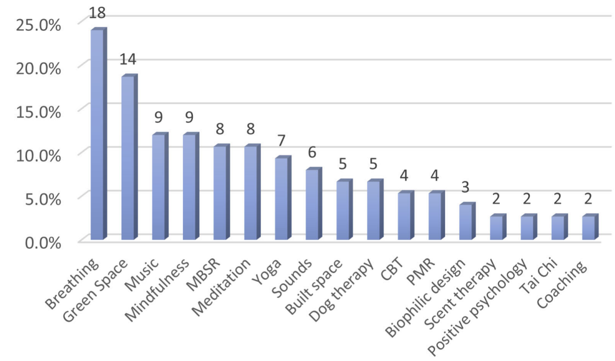

FIGURE 5. Intervention techniques used. Another techniques with the minimum frequency of use (1) are not included in the graph.

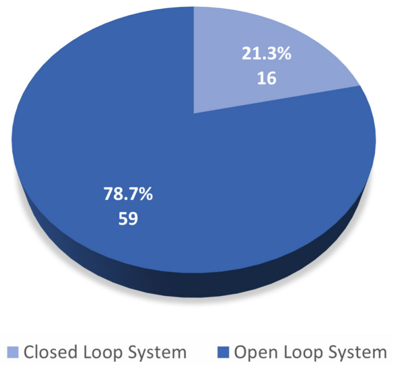

FIGURE 6. Type of control system. Closed loop systems included some sort of feedback during the intervention.

[34], [37], [45], [53], [56], [67], [72], [79]; video games in 3 experiments, which is 4.0% [54], [62], [78]; light equipment [31], [50] and haptic technology [28], [53] in 2 experiments each one, which corresponds to 2.7%; vapor machine [31] and automated recommendation systems based on artificial intelligence [18] in only 1 experiment each one, which is about 1.3%.

The duration of intervention is another important characteristic. We classified the intervention as training when the method includes multiple sessions over several weeks to teach specific skills, such as techniques of breathing or mindfulness; and non training when the participants are exposed to specific conditions in a few sessions, most often less than 4. Under this assumption, as shown in Table 5, 33 experiments (44.0% of the papers) were considered as training; and the other 42 (56.0% of the papers) were considered as non training.

6) TYPES OF CONTROL SYSTEM

As presented in Fig. 6, we categorized the reported experiments based on the concept of open and closed-loop control systems. Data show that 21.3% of the studies (i.e., 16 articles), included some sort of feedback during the intervention.

Biofeedback refers to the process in which the information of the measured physiological variable is presented to the individual through visual or acoustical signals. In this context, Table 6 presents the control action executed in the 16 articles within a closed-loop. Data show that all of them include biofeedback as closed-loop strategy. However, this strategy is also combined with a breathing guide, which is based on a coherence technique and virtual reality as shown in the last two rows.

IV. DISCUSSION

A. MAIN FINDINGS

The number of articles published and cited in last years has increased intermittently. This phenomenon suggests that more researchers in this specific field are supporting their work with technological tools, as analyzed in this review.

If we calculate the average of number of participants enrolled in the experiments, excluding the work that uses archival information [25], we get a mean of 56.6 individuals. Thus, a range between 1 and 75 could be considered as common in this kind of research. However, the application of machine learning techniques could imply increasing the participants to enhance the training process, which can potentially work better with large amounts of data.

Psychological tests are frequently used in most articles. This highlights the importance of this kind of measurements in the stress detection, which might become a key issue in the design of an experimental method for further research. The results also show that almost a half of articles use stressors to elicit acute stress during the experiment. Although Trier Social Stress Test and its variants are the most used ones, the results show multiple standardized tests that could be used for this purpose.

Overall, physiological measures related to cardiac activity appear to be the most common signals used in the articles analyzed. This type of measurements are mainly used to calculate hearth rate variability, which is closely related to stress recognition. The simple measurement process and the possibility to extract multiple indexes in time and frequency domain, could be some reasons for this trend. On the other hand, even though other physiological signals have a lower frequency of use, it seems very promissory to include in stress management systems. Measurements such as EDA, BR, EMG and ST are easy to implement. Acquisition devices usually have multiple channels to record information from different variables, resulting in systems with a high amount of data.

It is worth noting the importance of signal processing as an essential part of the research. Techniques such as filter application, domain transformation, features extraction, or application of machine learning models are some procedures which need special attention because these contribute to obtain a successful system. The results indicate that

TABLE 5. Type of intervention according to the duration of the experiments.

Type of intervention	References	No. of articles
Training	[5], [15], [17], [24], [26], [27], [30], [35], [37], [39], [42], [43], [45]–[47], [50]–[52], [57]–[60], [66], [71]–[75], [78], [81], [82], [84], [86]	33
Non training	[16], [18]–[23], [25], [28], [29], [31]–[34], [36], [38], [40], [41], [44], [48], [49], [53]–[56], [61]–[65], [67]–[70], [76], [77], [79], [80], [83], [85], [87], [88]	42

TABLE 6. Control action in the experiment of articles with closed loop.

Control action	References	No. of articles
Information of the variable (Biofeedback)	[19], [32], [34], [37], [43], [52], [62], [63], [74], [78]	10
Breathing guide and biofeedback	[30], [31], [50], [66], [75]	5
Modification on virtual reality experience and biofeedback	[45]	1

intervention techniques to manage the stress are quite diverse, including different kind of therapies, exposition to multiple types of spaces, or application of varied stimuli. Moreover, the relevance of breathing is remarkable, since other techniques such as mindfulness, MBSR, or Yoga, also include this component. Consequently, a lot of interventions are based on skills acquisition through an instruction process, which becomes a training exercise depending on its duration. On the other hand, techniques focused on modification of stimuli are used in the short term.

Nowadays, the use of laptops is a basic need and has become essential in research, and the application of this equipment, implicitly or explicitly, is presented in the experiments of all articles. Likewise, devices such as TVs, tablets, headphones, or speakers, are also frequently employed in this kind of procedures even though the specific use is not explained in detail. On the other hand, virtual reality, smartphone apps, haptic devices, or artificial intelligence support, which could be considered as novel technologies, seem to be very useful to manipulate stimuli, obtaining stress management control systems.

On the whole, the analyzed stress-management interventions are mainly open-loop systems, that is, there is no feedback. However, our interest is aimed to those closed-loop systems, which is only used in 16 articles. All these articles are based on biofeedback, sometimes used along with another basic control action such as breathing instruction or parameter modification in a virtual reality environment. Since biofeedback is based on the presentation of information of any variable, it is common that the control action depends on the skills of the subject to reduce stress.

According to the concept described in the Background and motivation section of this article, in a closed-loop system or feedback system, the controller uses the output of the plant to adjust its actions, unlike an open-loop control system. For example, in biofeedback, the plant is the individual himself to whom his physiological information is shown. The control actions depend on the individual's skills to manage stress. If the subject uses his own physiological information to adjust his actions to reduce stress, then this process can be considered as a successful closed-loop control system. Fig. 7 shows a diagram of a feedback control system in the context of stress management.

B. BIBLIOMETRIC ANALYSIS

We sought a complementary analysis applying the VOSviewer tool to conduct a bibliometric analysis. VOSviewer is a software to construct and view bibliometric maps [89], and analyze co-authorship, co-occurrence, citation, bibliographic coupling, and co-citation. To identify the topics of research, we applied a co-occurrence analysis of the author keywords to the final 75 articles included in this review. To develop the graph, we chose a threshold of a minimum number of occurrences of 3, and we used the keywords "stress reduction" and "stress management", which can be considered as synonyms. Thus, a total of 17 keywords were included in the resulting graph presented in Fig. 8. In this undirected graph, the nodes correspond to the keywords, the edge between two nodes corresponds to the co-occurrence of those keywords in a same article, and the weight of that edge corresponds to the number of articles with that co-occurrence. In addition, the thickness of the lines depends on the weight of each edge. Regarding colors in the graph, each one represents a cluster of keywords that could be used to determine the main topics of the field and the relationship between them. VOSviewer applies its own clustering technique, which is a variation of the function of modularity that includes weights and parameters [90].

The keywords in the graph are closely related to the results obtained in the above section. As expected, the word "stress" is the most important because it is the central axis of the search, as well as "stress management". We can identify 4 keywords related to physiological signals: "heart rate variability", "heart rate", "blood pressure", and "cortisol". Previously, we determined the importance of HRV calculation in stress detection from ECG and PPG measurements, which is reflected in the size of the

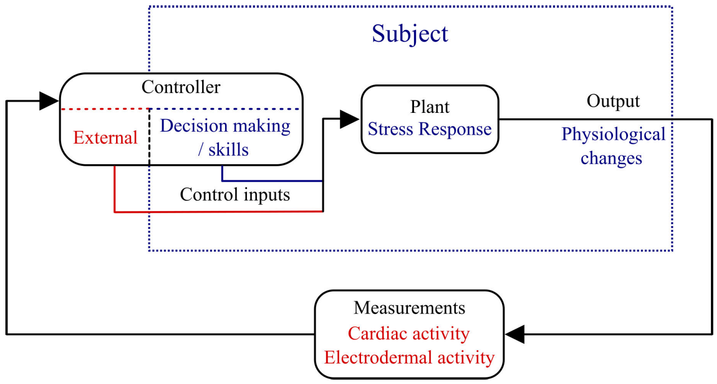

FIGURE 7. Block diagram of a stress management closed-loop control system. The terms in black color refer to the control theory concepts. Specific terms for stress-management closed-loop control system are highlighted in blue (part of the subject) and red (external to the subject).

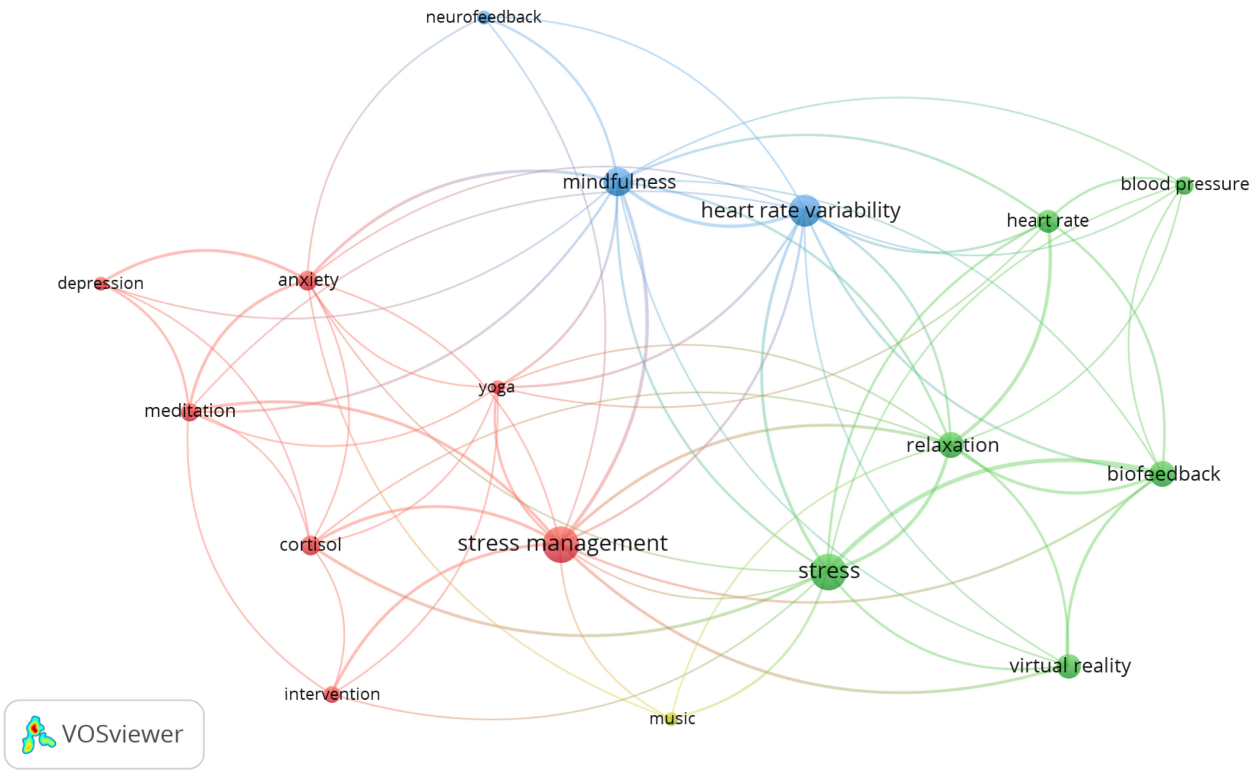

FIGURE 8. Co-occurrence of keywords graph in VOSviewer. Graph of author keywords of the 75 articles included in the review with a threshold of 3 occurrences.

corresponding node. Although cortisol was not included in the review analysis, it was applied to a significant number of articles. Different intervention techniques such as music, mindfulness, yoga, meditation, and biofeedback were identified in both the PRISMA protocol analysis and the VOSviewer co-occurrence analysis, showing consistency in the results. The presence of the keyword "virtual reality" in the graph emphasizes that it is a novel tool that could be used as part of the intervention technique. Finally, the graph seems to confirm that the application of control theory is absent in current stress management research, as well as machine learning techniques.

To determine the importance of each keyword, there are different metrics that could be used. Multiple normalized scores of centrality metrics and occurrences of keywords are shown in Fig. 9. One of the simplest and most commonly

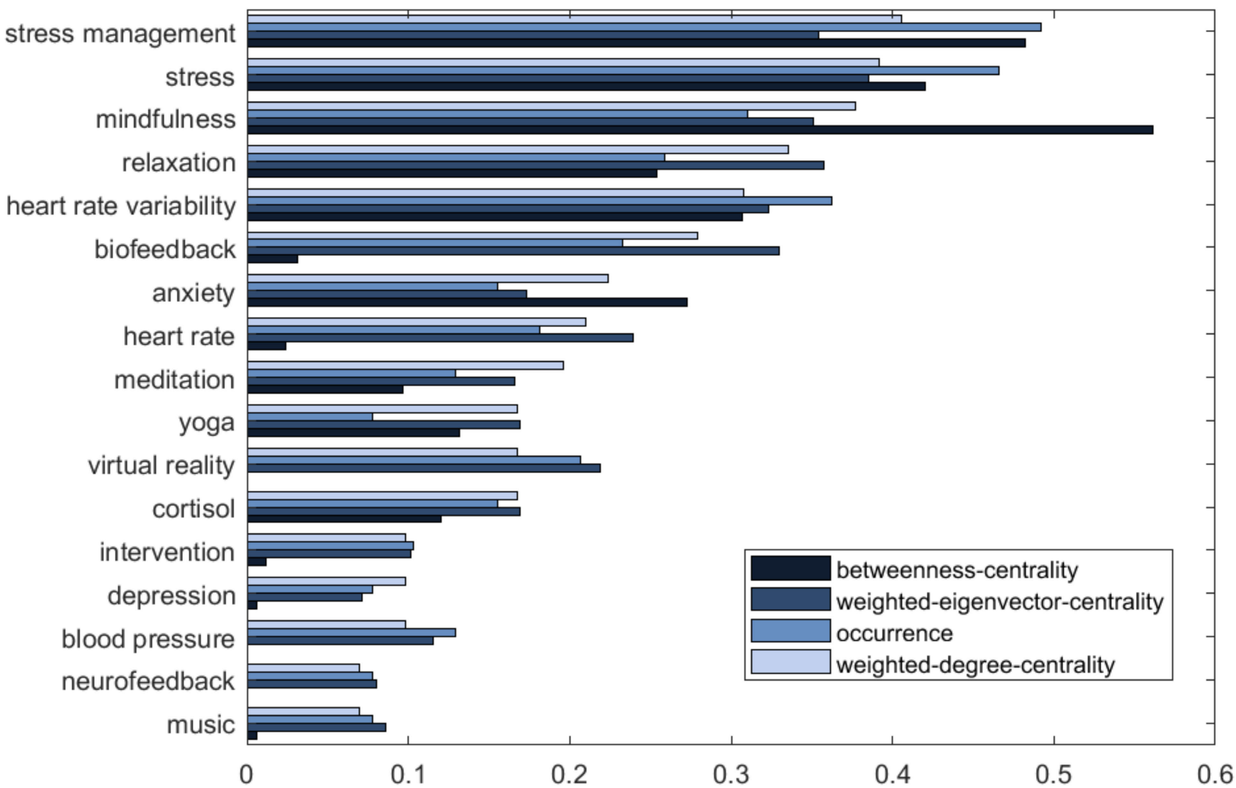

FIGURE 9. Centrality metrics and occurrences of co-word graph. From the lightest to the darkest, the bars correspond to weighted-degree-centrality, number of occurrences, weighted-eigenvector-centrality, and betweenness-centrality (All scores are normalized).

used index is the occurrence of each keyword, which does not consider the relationship between words. In contrast, the weighted-degree-centrality score considers not only the number of links but also the weight of edges, being an important parameter in the analysis. To calculate this score, we used Matlab with the selected keywords and the VOSviewer network files. In the VOSviewer software, this score is called the Total Link Strength, and it is selected to set the size of each node in Fig. 8. Also, we calculated the weighted-eigenvector-centrality score using the same procedure in Matlab. While degree centrality only takes into account the links between keywords, eigenvector centrality also takes into account their relevance [91]. In other words, this normalized score rises if the word is linked to other words with high score. Another included metric is betweenness-centrality, that is a measure of the times that a node is part of the shortest paths between pairs of nodes.

For the complete non-normalized metrics calculated using Matlab, see Appendix. According to the amount of links and its weights, weighted-degree-centrality scores establish "stress management", "stress", and "mindfulness" as the most important keywords in the graph. The same first two keywords and "relaxation" have the highest weighted-eigenvector-centrality scores, taking into account the correlation of relevant keywords. Likewise, betweenness-centrality states the importance of the same nodes "stress management" and "stress", also highlighting a keyword related to an intervention technique that is "mindfulness".

There are also global metrics to describe the topology of the graph, such as the clustering coefficient. This coefficient represents the trend to produce highly coupled neighborhoods in the network [92], with values between 0 and 1 for poorly and fully connected graphs, respectively.

The average clustering coefficient of the graph is 0.7314. Although this average takes into account the amount of vertex triplets that are linked in the network, it does not consider the edge weights for the connectivity analysis of the graph. In contrast, the weighted clustering coefficient includes the number of closed triplets and their importance in the connectivity of the vertex [93]. This consideration is possible by considering the edge weights in each triplet, obtaining an average weighted clustering coefficient of 0.7691, slightly higher than the unweighted coefficient. This value suggests that this co-ocurrence network has a

TABLE 7. Articles that include limitations.

Limitations	References	No. of articles	%
Included	[5], [15]–[17], [20]–[26], [28]–[31], [33]–[35], [37], [40], [41], [43], [44], [47], [48], [50]–[60] [62]–[64], [66]–[76], [78], [79], [81], [82], [84], [85], [87], [88]	58	77.3
Not included	[18], [19], [27], [32], [36], [38], [39], [42], [45], [46], [49], [61], [65], [77], [80], [83], [86]	17	22.7

high level of connectivity, which could represent that the seventeen keywords have a close relationship in the analyzed articles.

C. LIMITATIONS

It is worth mentioning that this review does not include a meta-analysis. Therefore, we did not include a detailed description of the indices, parameters, and features of the different signals analyzed in each article. Moreover, several articles do not report detailed information on technical characteristics of the measurement equipment and signal processing, such as sampling frequency, sensor resolution, and filters. Along the same lines, we focused on the description of the intervention techniques but we did not implement a quantitative comparison of the results since every method provides quite different conclusions.

Although we tried to include different expressions related to stress management, it was necessary to use a specific search equation due to the multiple meanings of the word "stress" in very different disciplines. In this search process, we only considered papers published as English language articles and we focused on subjects without any special condition such as hypertension, cancer survivors, multi-sclerosis patients, transplant patients, autistic, war veterans, or military. There are several studies focused on cortisol measurements that were not included in this review because only studies that involved automated physiological measurements and an explicit number of participants are considered.

In the screening process, 23 articles were not retrieved due to licensing limitations. Even though three researchers (AAJ, AP, LFG) defined the eligibility criteria and decided on complex cases, only one researcher (AAJ) performed the classification of articles and the data extraction, which implies a risk of bias in the process. In addition, Table 7 presents the articles that include research limitations, which is an important indicator of the quality and reliability of the data and results.

V. CONCLUSION

In this article, we presented a systematic review applying the PRISMA protocol, focused on the identification of technology aids for stress management systems. We searched for experimental research works that included automated physiological measurements, intervention techniques and control actions. The high quality of the included articles is ensured by the application of the eligibility criteria following the protocol.

The results showed that HR, ECG, BP, and EDA were the most used physiological signals to detect stress. Furthermore, signals related to cardiac activity were widely applied by calculating HRV. Also, a lot of intervention techniques were identified and characterized, where breathing therapy, green space stimuli, music, and mindfulness were the most used. The analyzed experiments included several technological tools in each phase. In the detection phase, different electronic devices were used to measure physiological variables, and a couple of articles applied machine learning techniques to process the data. In addition, innovative tools such as virtual reality, haptic technology, video games, or light equipment were applied to intervention techniques, as well as traditional devices such as screens, laptops, smartphones, audio equipment, or tablets.

Most of the stress management systems discussed in this review were open-loop control systems. On the other hand, the closed-loop control systems were focused on the concept of biofeedback, where the physiological information is showed to the subject, but there is not an automated external controller. Consequently, the stress response depends on the skills of the individual. We did not identify the application of any technique of theory of control in the 16 closed-loop control systems. This means that there was not external controller producing control inputs in any feedback system.

In consequence, we have identified different opportunities for future research:

- Although studies related to application of machine learning for stress detection have been developed, these techniques are still little applied in stress management systems. As a result, the coupling of automated stress detection to these systems is an open research field, focusing on selection of physiological variables, individually or in groups, measurement procedures, signal adequacy, feature extraction, and processing with machine learning.
- The selection of the intervention technique based on characteristics such as duration, availability of parameter manipulation, equipment necessary to implementation, or experimentation protocol, is essential to achieve a successful system, and should be object of study.
- The application of control techniques to develop a closed-loop system according to control theory could be a promising approach with major impact on stress-management systems. Thus, the capability to modify parameters of the intervention technique based on measured stress levels require an understanding of the theory of control systems and the chosen intervention technique.

TABLE 8. Centrality metrics of co-word graph.

Keyword	Occurrence	Weighted-degree-centrality	Weighted-eigenvector-centrality	Betweenness-centrality
anxiety	6	16	0.0469	6.6012
biofeedback	9	20	0.0893	0.7667
blood pressure	5	7	0.0313	0.0000
cortisol	6	12	0.0458	2.9179
depression	3	7	0.0193	0.1429
heart rate	7	15	0.0649	0.5750
heart rate variability	14	22	0.0875	7.4345
intervention	4	7	0.0275	0.2917
meditation	5	14	0.0449	2.3429
mindfulness	12	27	0.0951	13.6010
music	3	5	0.0233	0.1429
neurofeedback	3	5	0.0219	0.0000
relaxation	10	24	0.0968	6.1512
stress	18	28	0.1044	10.1690
stress management	19	29	0.0959	11.6770
virtual reality	8	12	0.0593	0.0000

APPENDIX

See Table 8.

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ALVARO A. JIMÉNEZ-OCAÑA received the B.S. degree in electronics engineering from Universidad de Nariño, Pasto, Colombia, in 2009. He is currently pursuing the Ph.D. degree in engineering with Universidad de los Andes, Bogotá, Colombia.

His research interests include physiological signal processing, machine learning, deep learning, and feedback for stress analysis.

ANDRÉS PANTOJA (Member, IEEE) received the Ph.D. degree in engineering from Universidad de los Andes, Bogotá, Colombia, in 2012.

He joined Universidad de Nariño, Pasto, Colombia, where he is currently an Associate Professor and the Head of the Department of Electronics. His research interests include dynamic resource allocation, distributed generation, distributed control in smart grids and buildings, and coordination in large-scale systems.

MARIO ANDRÉS VALDERRAMA received the Ph.D. degree in neurosciences from University Pierre and Marie Curie (Paris-VI), France.

He is currently an Associate Professor with the Department of Biomedical Engineering, Universidad de los Andes, Bogotá, Colombia. His current research interests include the development of instrumentation systems and on the application of different signal processing techniques to the study of brain activity in distinct physiological and clinical contexts.

LUIS FELIPE GIRALDO (Member, IEEE) received the Ph.D. degree in electrical and computer engineering from The Ohio State University, in 2016.

He is currently an Associate Professor with Universidad de los Andes, Bogotá, Colombia, and a member with the Center for Artificial Intelligence Research and Education, CINFONIA. His current research interests include leverage artificial intelligence and technology to address challenges with social impact.