Journal of Biomedical Informatics 59 (2016) 49–75

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Methodological Review

Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review

Ane Alberdi [a,*], Asier Aztiria [a], Adrian Basarab [b]

[a] Mondragon University, Electronics and Computing Department, Goiru Kalea, 2, Arrasate 20500, Spain
[b] Université de Toulouse, IRIT, CNRS UMR 5505, Université Paul Sabatier, Toulouse, France

ARTICLE INFO

Article history:
Received 5 March 2015
Revised 16 November 2015
Accepted 19 November 2015
Available online 28 November 2015

Keywords:
Stress
Early detection
Multimodality
Behaviour
Physiology

ABSTRACT

Stress is a major problem of our society, as it is the cause of many health problems and huge economic losses in companies. Continuous high mental workloads and non-stop technological development, which leads to constant change and need for adaptation, makes the problem increasingly serious for office workers. To prevent stress from becoming chronic and provoking irreversible damages, it is necessary to detect it in its early stages. Unfortunately, an automatic, continuous and unobtrusive early stress detection method does not exist yet. The multimodal nature of stress and the research conducted in this area suggest that the developed method will depend on several modalities. Thus, this work reviews and brings together the recent works carried out in the automatic stress detection looking over the measurements executed along the three main modalities, namely, psychological, physiological and behavioural modalities, along with contextual measurements, in order to give hints about the most appropriate techniques to be used and thereby, to facilitate the development of such a holistic system.

1. Introduction

Stress is a growing problem in our society. It is part of our daily life and many people suffer from it. We spend most of our time in the workplace, often with high workloads and time pressure, which contributes to increase our stress levels.

Stress is the second most frequent work-related health problem in Europe [1], preceded by musculoskeletal disorders which may also be a stress symptom in some cases [2]. In 2002, work-related stress cost € 20 billion to the enterprises of EU15[1] [3] and in 2005, 22% of working Europeans suffered from it [4]. According to a recent opinion poll [5], 51% of European workers confess that stress is common in their workplace and it is estimated that 50–60% of all lost working days in European enterprises are due to work-related stress and psychosocial risks [1].

1.1. Definition

Hans Selye defined stress as "the non-specific response of the body to any demand for change" [6]. Thenceforth, other definitions that take into account the coping abilities of each individual have been exposed [7], including the one of McEwen [8] that defines stress as "events, that are threatening to an individual, and which elicit physiological and behavioural responses". Regarding the occupational environment, work-related stress has been defined as "the emotional, cognitive, behavioural and physiological reaction to aversive and noxious aspects of work, work environments and work organisations. It is a state characterised by high levels of arousal and distress and often by feelings of not coping" [9]. "Work-related stress is experienced when the demands of the work environment exceed the employees' ability to cope with (or control) them" [1]. These demands are not only related to high workload or long working hours, but also to high perceived stress, low social support from colleagues and managers, or to the individual characteristics of each one like the education and competitiveness [10,11].

Therefore, work-related stress, which refers to the stress that has been caused by work, or at least, made worse due to work, [12] can be understood as a particular example of stress. It follows the same characteristics as general stress and its response patterns and effects can be evidenced, and accordingly, measured, in the same way.

1.2. Stress types and levels

Selye [6] distinguished the concepts "eustress" and "distress", as a positive and negative stress, respectively. Eustress appears

* Corresponding author. Tel.: +34 647504215.
E-mail addresses: aalberdiar@mondragon.edu (A. Alberdi), aaztiria@mondragon.edu (A. Aztiria), adrian.basarab@irit.fr (A. Basarab).

[1] EU-15 area countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom.

http://dx.doi.org/10.1016/j.jbi.2015.11.007
1532-0464/

with positive changes or demands that don't pose a problem for coping with or to adapt ourselves to the new situation. It can help us meet our goals and increase productivity [2]. Distress can be really harmful and can carry negative consequences. It is the most investigated aspect of stress and it is what in general terms, as well as throughout this paper, is understood by "stress".

Besides, three levels of stress can be distinguished depending on the time of exposure to stressors. Acute stress is the innate "flight-or-fight" response in face of short lasting exposure to stressors and it is not considered harmful [13]. Episodic stress appears when stressful situations occur more frequently, but they cease from time to time. It is associated with a very stressful and chaotic life [13]. Finally, chronic stress, which is the most harmful, takes place when stressors are persistent and long-standing, such as family problems, job strain or poverty [2].

In order to avoid stress to reach the highest level and help diminishing the risks [14], it is necessary to detect and treat it in its earlier stages, i.e. when it is still acute or episodic stress.

1.3. Long-term consequences

When work-related stress arises and it is not treated, it can cause big long-term physical and mental problems on the worker [4], but also economic losses in the companies.

Musculoskeletal disorders, depression, anxiety, increased probability of infections [15], chronic fatigue syndrome, digestive problems, diabetes, osteoporosis, stomach ulcers [3,16,17] and coronary heart disease are only some examples of chronic stress' long-term consequences.

These health problems bring consequences to enterprises, where absenteeism, staff turnover [4] and tardiness increase, decreasing the production. The problem of "presenteeism" also arises, where employees attend their workplace, but they don't work at 100% of their capabilities. Recently, the annual cost of absenteeism and presenteeism has been estimated at € 272 billion and the annual cost for loss of productivity at € 242 billion [3].

Given the importance of stress' long term consequences, the need of avoiding it as much as possible becomes evident. It is of great significance to detect stress in its early stages, before damages being caused. The scientific community is aware of this and much progress has been done in the last years towards the development of an automatic stress measuring system. Nevertheless, a reliable real-time stress measuring system, which is unobtrusive and completely transparent for the user has not been still created. The objective of this paper is to review the research done in this area to ascertain the paths to be followed in the future in order to get such an unobtrusive real-time stress monitoring system. For this purpose, the stress measurement techniques that have been used or that could be used in an office environment are reviewed, as well as the detection results of the state of the art in order to help selecting the best signals and features, and the methodological techniques that should be used for creating a stress monitoring system based on these measurements. Sharma and Gedeon [18] published a survey in automatic stress detection in 2012, where objective ways for measuring stress using physiological and physical information were explained, as well as information about the published stress data sets, monitoring systems and stress scales used in the literature. Some of the feature extraction and computational techniques were also exposed. Nevertheless, stress' multimodal nature was not considered in all its fullness and relevant measurement techniques based on contextual and behavioural information were ignored. Herein, an upgrade of the state of the art since its publication is given, in addition to a broader view of the multimodal nature of stress, which provides a different point of view of stress measurements, giving a clue for overcoming nowadays' obstacles.

This paper is structured as follows. In Section 3 the multimodality of stress is introduced and state of the art stress measuring methods are explained for each modality. In Section 4, stress elicitation methods are briefly described. Farther, in Section 5, a framework for an ubiquitous stress monitoring system for office environments is proposed based on the current technology and in Section 6 the challenges that are still open for this purpose are reviewed. Finally, in Section 7 a conclusion about the state of the art is given along with clues for future work.

2. Methods

The following review of the state of knowledge concerning stress detection, and, in particular, mental stress detection, was undertaken to address three specific goals:

1. To review the signals or measurements, as well as the variety of features, that can currently be used in order to measure mental stress levels of individuals, starting from the most widely accepted methods, to the new emerging ways.
2. To compare the accuracies that can be achieved with each signal or measurement, so as to help to decide among the most suitable signals for each situation.
3. To highlight the steps that should be followed in order to achieve a ubiquitous stress detection system for office workers.

To attain these goals a simple literature review was performed, with the following search strategy and inclusion criteria.

2.1. Search strategy

Publications were retrieved by means of a computerised search of the Compendex and Inspec databases via Engineering Village [19] and of the PubMed database [20] in order to find relevant studies published in English from January 2004 to date.

The review was carried out in an iterative way: first, a global point of view of the current state in stress detection was searched. The search terms used for this step were: "stress" AND "detect*" OR "diagnos*" OR "measure*" AND "survey" OR "review". Controlled terms were used in order to discard all the publications related to non-relevant domains. After removing duplicates, 101 results were achieved. Titles and abstracts of the remaining papers were reviewed, rejecting the ones that did not work with human beings or focused on aspects of stress other than the measurement. Only eight papers were considered for further reading.

Once identified and understood the main concepts in current stress detection, the search terms were refined so as to focus on and identify the several domains and modalities of the measurable stress responses. The search terms in this step included "multimodal" OR "multi-modal" OR "taxonomy" AND "stress" AND "detect*" OR "diagnos*" OR "measure*" OR "anal*" OR "identif*" OR "model*". The non-relevant and duplicated references were excluded and 64 articles were retrieved. After title and abstract analysis, 42 were selected for further reading where those that did not accomplish the inclusion criteria were discarded.

After identifying the main domains and modalities involved in the current state of stress detection, a more specific search was carried out for each one of the domains. The combination of search terms used were the following: "mental stress" OR "workload" AND "detect*" OR "recogn*" OR "identif*" OR "model*" OR "anal*" OR "diagnos*" AND "physiolog*" OR "behavio*" OR "psycholog*" AND "accura*". A first set of 1159 study abstracts was retrieved for assessment. Controlled vocabulary terms were used in order to exclude publications related to non-relevant research areas and duplicates were rejected. The bibliographies of all relevant articles and review papers were also hand-searched. The titles and abstracts of the remaining articles were reviewed in applying the inclusion criteria. Thirty papers were in-depth read and the 10 which reported the best accuracies in detecting stress were selected.

A summary of the literature review methodology used is presented in Fig. 1.

2.2. Inclusion criteria

All the selected papers were original studies and journal or conference articles, written in English and published from 2004 onwards. For the first step of this literature review, only the papers in where objective stress measuring systems for human beings were reviewed were accepted. In the second step only works in where a taxonomy of stress detection systems and stress responses was presented were in-depth analysed. Finally, for the third step of the literature search, the inclusion criteria were the following: studies of diagnostic accuracy of stress using at least physiological or behavioural data and validated by means of psychological tests and self-report questionnaires or hormonal biomarkers, total subjects in the study at least nine and sufficient data reported either directly or indirectly to enable the accuracy table construction.

2.3. Data extraction and quality assessment

A data extraction spreadsheet was created for collecting data from the papers. Each one of the selected papers was fully read and assessed by one of the authors, whereas the results were verified by all of them. Disagreements were resolved through discussion.

3. Measuring stress levels

The Sympathetic Nervous System (SNS) provokes the stress response in humans [21], carrying psychological, physiological and behavioural symptoms [22]. Throughout this paper, the following definitions are considered for these groups of responses. Psychological is understood as "of or relating to the mind or mental activity" [23] and they do not involve the execution of an action. Physiological responses are part of the normal functioning of a living organism or bodily part [24], therefore, they are non-voluntary actions or responses, and very hard or impossible to notice by external observation. Behavioural is interpreted as "the manner of conducting oneself" [25], so that, unlike physiological responses, they involve an action that could be controlled or changed relatively easily in a voluntary way, and can be externally observed.

Psychological responses comprise the increase of strong negative emotions, such as anger, anxiety, irritation or depression [4] and can also make our emotional responses more intense feeling more worried, frustrated, and hostile with the consequent effects on our relationships [16].

From a physiological point of view, the increase of SNS activity changes the hormonal levels of the body and provokes reactions like sweat production, increased heart rate and muscle activation [15]. Respiration becomes faster and the blood pressure increases [17]. As a consequence of changes in the muscles which control the respiratory system and vocal tract, speech characteristics change too. Skin temperature decreases together with hands and feet temperature [26] and the Heart Rate Variability (HRV) decreases [27]. Moreover, pupil diameter can vary.

Finally, behavioural reactions include eye gaze and blink rate variations, in addition to changes in facial expressions or head movement [28]. When working in an office environment, interaction patterns with the computer can be affected, together with the General Somatic Activity or body's agitation level. Performance related to the accuracy and cognitive response, such as the logical thinking [16], attention and working memory can also be affected, leading to a decrease in productivity and tendency to mistakes. Some people may also abuse of tobacco, alcohol and drugs [1].

While the analysis of physiological changes has been the objective of many stress researches, other areas such as behavioural changes have not been enough studied. Furthermore, as context affects the stress response of the individuals, measurable contextual information may also provide important clues about individuals' stress levels. Fig. 2 shows the multimodal nature of stress. It can be seen that stress is affected by the context, which in turn depends on the personal characteristics of the subject and on circumstances that are not subject-dependent like events, places or moments. Stress responses are evidenced, at least, in the three aforementioned modalities, and thereby, an efficient stress detection system should take advantage of as most evidences as possible.

3.1. Psychological evaluation

Psychological evaluation of stress can be carried out by means of self-report questionnaires or by being interviewed by a psychologist. The former is one of the most widely used ways to measure stress levels in humans and it is considered a reliable method. The Stress Self Rating Scale (SSRS) [29], the Perceived Stress Scale (PSS) or the Stress Response Inventory (SRI) are some examples. However, these questionnaires only offer information about current stress levels of the user and not about the stressors nor about the evolution of the stress levels. These tests can be taken from time to time, but may not be suitable for detecting the subtle changes which could indicate an early stage of a major problem. Actually, they are only taken when the affected himself or the people around him realise or suspect about the severity of the situation, and this is too late in the vast majority of the cases. Furthermore, questionnaires are subjective and require the full attention of the user. "People can suffer lapses in memory about the emotional tone of a day in as little as 24 h" [30], which means that we are not always aware of our real stress levels and that methods such as self-report questionnaires could sometimes lead to an incorrect stress level measurement.

3.2. Physiological signals

Physiological signals can provide information regarding the intensity and quality of an individual's internal affect experience [31]. Hormone measurement is considered a reliable way for measuring stress' physiological response, but entails some drawbacks. While the relationships between some physiological signals such as Heart Rate Variability (HRV) and salivary cortisol levels have been proven [32], others need further research.

3.2.1. Hormone levels

The stress response changes the endocrine and immune systems by releasing adrenaline and cortisol hormones [18] from the adrenal cortex and the adrenal medulla, respectively. Cortisol levels follow a daily cycle in healthy people, characterised by peak values in the morning, decreasing them during the whole day and reaching the lowest values at night. Under stress, the ability to regulate cortisol levels decreases [32] keeping them high even at night [33] and changing the typical patterns [34]. Consequently, people suffering from chronic stress have elevated cortisol levels. Cortisol levels are considered a reliable biomarker of psychological stress [32] and can be measured in blood, urine or saliva, being the latter the preferred by the researchers due to its non-invasive nature [34]. Nevertheless, cortisol levels measured in blood can offer better inter-individual differences [35].

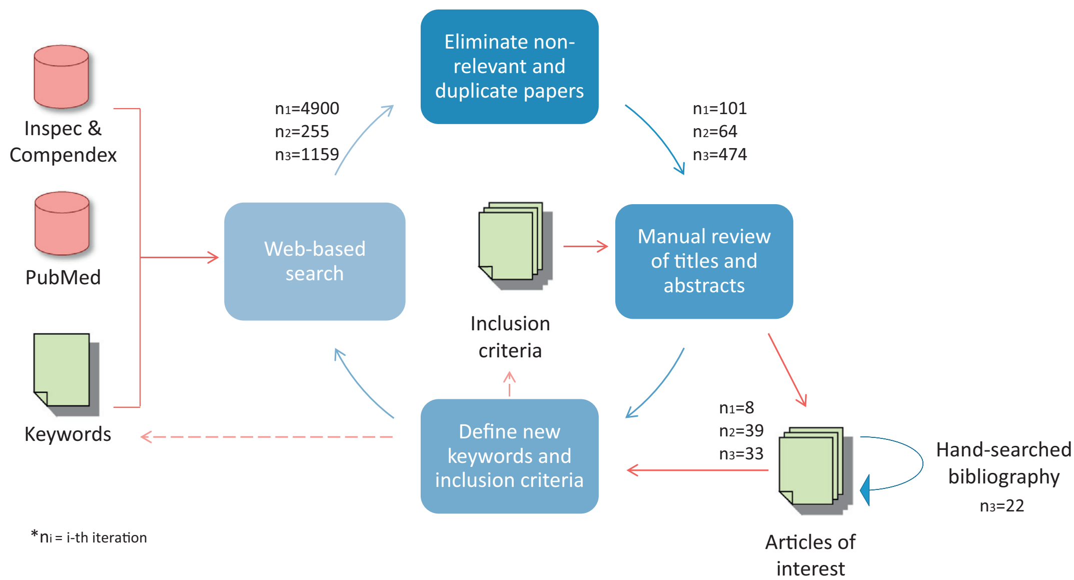

Fig. 1. Search methodology used for the literature review process.

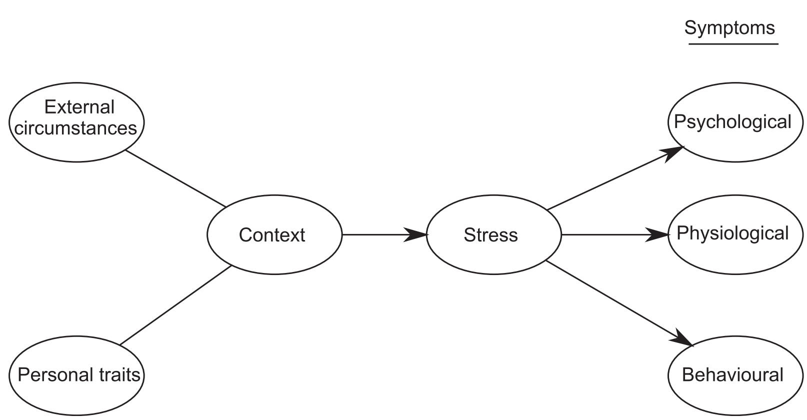

Fig. 2. The multimodal nature of stress. The figure is inspired from [28].

However, as well as psychological questionnaires, this method is not suitable neither practical for carrying out a continuous monitoring of stress levels. Some researches [27] suggest that continuous sampling of such biomarkers is not realistic. Actually, the same as with the preceding method, this kind of measurements are only done when the affected himself or the people around him realise or suspect about the severity of the situation. Changes can be detected performing measurements every several months and comparing results, but this may not be enough to detect subtle changes related to early stages of stress [36]. As Sharma and Gedeon [18] state, these methods "require major human intervention, including manually recognising and interpreting visual patterns of behaviour". Unfortunately, individuals may not recognise these signs and let them go untreated [17]. Vizer et al. [36] also suggest that "current tests are usually administered in a physician's office or a rehabilitation facility, causing inconvenience for the patient, using valuable healthcare resources, and making frequent monitoring unrealistic". Hormonal measurements are intrusive, costly and slow methods of analysis [37]. Consequently, the appreciation of being over-stressed often comes too late, when health problems already manifest themselves [38].

3.2.2. Electrocardiogram (ECG)

The electrocardiogram (ECG or EKG) is "the recording on the body surface of the electrical activity generated by heart" [39]. It is one of the most used signals in stress detection research because it reflects directly the activity of the heart, which is clearly affected by ANS changes [40]. An ECG can be easily measured placing some electrodes on specific places of the body and measuring the potential difference. The number of electrodes and their positions can vary, but one of the most simple and effective ways is the Lead-II configuration, which consists of placing three electrodes: one on the right arm, one on the left arm and the last one on the left leg. The most typical and useful features computed with an ECG are probably the ones related to the Heart Rate Variability (HRV).

Many stress researches have used ECG signals successfully.

An example could be the work of by Cinaz et al. [41], who considered a 3 class classification problem to separate office workers' mental workload into low, medium and high groups using only an ECG signal and nine HRV features (eight time domain features and the LF/HF ratio), achieving correct predictions for 6 out of 7 subjects using Linear Discriminant Analysis (LDA) [42] classification.

Wijsman et al. [15] measured ECG along with skin conductance, respiration and EMG of the Trapezius muscles. Using a very reduced set of features (only five features) extracted from those signals, including Heart Rate, they achieved an accuracy of 80% and 69.1% in the non-stress and stress detection respectively.

In the study executed by Palanisamy et al. [43], HRV, ECG, EMG, EDA and ST were measured and a total of 148 features were extracted. Classification accuracy of each one of the signals was analysed instead of creating a classification system based on the whole set of signals. Results showed that compared to the other signals, ECG and HRV performed well in stress detection. Precisely, a maximum classification rate of 93.75% was achieved with HRV, followed by ECG with 76.25% and the minimum classification rate with EDA signals, 70.83%.

Melillo et al. [44] investigated the effect of stress on HRV parameters under real-life conditions, unlike most of the State of the Art works which have analysed them in laboratory settings. They selected two critical moments to measure students' ECGs: during an oral exam and after holidays. They used 13 non-linear HRV features and LDA to classify stressed and relaxed situations, and an accuracy of 90% was achieved, affirming the potential of these signals for the real life stress detection.

All these results suggest that ECG and HRV features allow distinguishing between different mental workload and stress levels.

Furthermore, it has been proved that ECG can be monitored continuously. Okada et al. [27] developed a continuous stress monitoring system for office workers based on ECG recordings and helped by an accelerometer used for activity recognition and movement artefact removal. RRI (R-R Interval), HRV spectrum and Tone and Entropy information were extracted from the ECG. After a 3 day experiment, the availability of the system was validated and thus, the feasibility of a continuous monitoring system was approved. However, the developed system needed an offline analysis to be carried out by an expert.

3.2.2.1. ECG features. ECG has been studied for extracting features like the mean, standard deviation, power and energy of the preprocessed raw data [43], but it is more frequently used to extract information about Heart Rate (HR) and Heart Rate Variability (HRV).

HR is defined as the number of heartbeats per minute. Worldwide scientific research has shown that heart rate increases during stressful times [22]. It is frequent to analyse the HR by computing the Mean, Standard Deviation, and minimal and maximal values over time[45,46].

HRV, which is the temporal variation between sequences of consecutive heart beats [47], is probably the most commonly used feature in stress detection. It is considered to be a non-invasive biomarker that reflects the activity of the sympathetic and vagal components of the Autonomic Nervous System, in the low (LF) and high frequency (HF) power bands respectively [47,48]. Healthy people's HRV varies continuously, following sinus cycles that reflect a balanced sympathovagal state, but when ANS' activity is disturbed, the resulting sympathovagal activity imbalance appears as a decreased HRV.

Hjortskov et al. [49] concluded that HRV is a sensitive indicator of mental stress in office environments. They have proven that HF values of HRV decreased in stress situations at the same time as the ratio LF/HF increased. The inverse correlation between salivary cortisol levels and HRV has also been demonstrated [32]. Healey et al. [50] concluded that this feature is the most relevant one after the EDA measures for real-time stress recognition in a driving task.

HRV can be analysed both in the temporal and in the frequency domain.

In the temporal domain, statistical and geometrical parameters are computed. The most common parameters are the mean value and the Standard deviation of RR intervals (SDRR), the Root Mean Square (RMSSD) and the standard deviation (SDSD) of RR intervals' successive differences, the standard deviation of the averages of NN intervals in all 5-min segments of the entire recording (SDANN), the percentage of the number of successive RR intervals varying more than 50 ms from the previous interval (pNN50), the HRV triangular index (TI) and the triangular interpolation of RR interval histogram (TINN) [27,48,51]. Palanisamy et al. [43] analysed three HRV frequency bands, namely 0.04–0.15 Hz, 0.15–0.5 Hz and 0.04–0.5 Hz, using kurtosis, skewness, second, third and fourth-order cumulant features.

In the frequency domain, the most widely used method for analysing HRV is computing the LF/HF ratio [49,52,53] but HF/All ratio is also common [27] as well as the total energy of the spectrum and energy of certain frequency bands, namely Ultra-Low (ULF), Very-Low (VLF), Low (LF) and High (HF) bands [48]. Healey et al. [50] also considered the (LF + MF)/HF ratio.

Non-linear measurements such as entropy, which measures the degree of a system's disorder, are also used [27,54,55]. Entropy (E) can provide information about the regulation mechanisms of heart rate when applied to the HRV. Approximate Entropy and Shannon Entropy are the most frequent ones in the literature. Complexity (C), which measures the randomness of RR intervals and tone (T) [27], which represents the sympathovagal balance, are also computed. PoincarT Plot is also commonly used to extract its SD values, and other non-linear measures such as line-lengths in Recurrence Plots and fluctuation slopes based on Detrended Fluctuation Analysis (DFA) have been used by Melillo et al. [44].

3.2.3. Electroencephalogram (EEG)

An electroencephalogram is a test that measures the electrical activity of the brain. It is monitored by placing an array of electrodes on the subject's scalp so that the electrical fluctuations are recorded. The number of electrodes depends on the application. EEG signals can be divided into four main frequency bands: Alpha (8–13 Hz), Beta (13–30 Hz), Delta (0.1–4 Hz) and Theta (4–8 Hz).

Alpha waves reflect a calm, open and balanced psychological state, so Alpha activity decreases in stress situations [32]. Besides, Beta activity reflects cognitive and emotional processes [56] so it increases with mental workload and thus with stress. Stress has also been related to changes in Right Frontal Activity (RFA) provoking frontal asymmetry. Whether stress can be reliably evaluated from the EEG has been unclear [32] but there are some researches that suggest its validity.

Seo et al. [32] analysed the relationship between EEG, ECG and cortisol levels when measuring chronic stress, using the Stress Response Inventory and the Self Assessment Manikin tests as ground truth. A significant positive correlation was found between the cortisol levels and the high Beta activity at the anterior temporal sites when people kept their eyes closed, affirming the aforementioned relationship between the Beta band and stress. Furthermore, the mean high beta power at the anterior temporal sites of the stress group was found to be significantly higher than of the non-stress group.

Rahnuma et al. [57] recorded EEG from Frontal, Central and Parietal lobes of the scalp, in order to create an emotion recognition system based on Russel's model of affect [58]. This model describes all the emotions based on arousal and valance, mapping stress to a negative valence and a very negative arousal coordinate. An accuracy of 96.4% was achieved, suggesting that emotions and stress detection is possible combining valance and arousal information obtained from EEGs.

Zhang et al. [59] monitored EDA, HRV and EEG signals of 16 subjects under cognitive load and in relaxed states. Subjective stress ratings based on the State-Trait Anxiety Inventory (STAI) were used as labels. Discriminative spatial-spectral EEG components were computed by means of a spatial-spectral filtering in the theta, alpha, low beta, mid beta and high beta frequency bands. Mean EDA and 10 time-domain features of the HRV were also computed. A large margin unbiased regression approach was developed in order to overcome the inter-subject variability that may show these signals. Results show that EEG features extracted using the proposed filtering technique outperformed both EDA and HRV features in discriminating both situations, with 87.5%, 75% and 62.5% accuracies respectively.

3.2.3.1. EEG features. From EEG signals, mean amplitude, mean amplitudes of Event Related Potential (ERP) components, mean power spectra of Beta [53] Alpha, Delta and Theta frequency bands [60] and mean power ratios are probably the most frequently computed features. Fractal dimension, which is a measure that provides information of the space filling and self-similarity, has also been used in various researches [60,61]. Other potential features can also be found in the literature, like the three Hjorth parameters (Activity, Mobility and Complexity) [60] which are time-based characteristics of an EEG, mean and standard deviation of the largest Lyapunov exponent (LLE) [62] and Higher Order Crossings (HOC) [61]. In addition, Kernel Density Estimation method has been used [57] for feature extraction, computing their mean and variance. Zhang et al. [59] also made use of some spatial-spectral features extracted using a specific filter bank common spatial pattern filtering technique.

3.2.4. Electrodermal Activity (EDA)

The Electrodermal Activity (EDA), also known as Galvanic Skin Response (GSR), Electrodermal Response (EDR), Electrodermal Level (EDL), Skin Condutance Activity (SCA) or Skin Conductance Response (SCR), is defined as a change in the electrical properties of the skin [63]. Under emotional arousal, increased cognitive workload or physical activity, the level of sweating increases, changing the skin properties, i.e. increasing conductance and decreasing resistance [16,40]. EDA can be measured placing two electrodes on the skin surface next to each other and applying a weak electrical current between them.

EDA is one of the best real-time correlates of stress [50]. It is linearly related to arousal [37] and it has been widely used in stress and emotion detection [21,30,38,50]. Even some researches consider EDA measures as ground truth for analysing the performance of other signals [16,37].

One of the most relevant stress related research was carried out by Healey et al. [50], where a real-live driving task was analysed with hand and foot EDA, together with three other physiological measurements, namely ECG, Trapezius muscle EMG and respiration. Three levels of stress were induced on subjects by making them drive through a highway (medium stress level), through a city (high stress level) and have rest periods (no stress). 22 features were extracted and LDA classifier was used achieving a recognition rate of 100%, 94.7% and 97.4% for low, medium and high stress levels, respectively. From the viewpoint of a continuous monitoring of stress levels, EDA and HRV were found to be the best correlates of real-time stress.

De Santos Sierra et al. [45] created individual stress templates for 80 individuals using EDA and HR signals and a fuzzy logic algorithm. Accuracy of 99.5% was achieved for a two class classification problem, suggesting that both signals have really the potential for detecting stress levels precisely and in real-time.

Other researches are not consistent with these results. Seoane et al. [64] suggest that cardiac and respiratory activity is better stress indicator than EDA, ST and speech and Palanisamy et al. [43] affirm that EDA offers lower classification accuracy than ECG, HRV, EMG and ST signals.

3.2.4.1. EDA features. When getting information from an EDA signal, statistical values like the mean amplitude, standard deviation (SD) of the amplitude, minimum and maximum values and the Root Mean Square (RMS) are typically used [21,40,45,51,65].

Latency between the stress stimulus and the response, rising time (tRise), difference between first value and the maximum (DiffMax), position of maximum (MaxPos), position of minimum (MinPos), difference between first value and the maximum (DiffMax), difference between value and the minimum (DiffMin), zero crossings (ZC), number of peaks [66], peak height [21,30] and half recovery time (tRecovery) also represent the typical electrodermal activity under stressful stimulus.

Onset (O), peak (P), duration (D) and magnitude (M) of the orienting responses were measured by Healey et al. [50] as well as the total number of responses, the sum of magnitudes, the sum of response duration and the sum of the estimated areas under the responses (areaResp). Orienting response refers in this case to the immediate response to stress stimuli, which is reflected as a peak in the EDA signal. Kurtosis, skewness and smoothed 1st derivative average (DiffAvg) have also been used by Giaukomis et al. [67] as well as the SCR amplitude (Aq) and duration (Dq) quantile thresholds at 25%, 50%, 75%, 85%, and 95% and the average area under the rising half of SCRs (areaRise).

3.2.5. Blood Pressure (BP)

Blood Pressure is the pressure of the blood against the inner walls of the blood vessels and it can be measured using a stethoscope and a sphyngomanometer [68].

It is proven that stress increases blood pressure [22] depending on the experienced stress levels. Nevertheless, Hjortskov et al. [49] state that blood pressure is not as good indicator as HRV to detect stress situations. They discovered an increased blood pressure during the whole experiment, both in stress situations and control situations, remarking no differences, i.e. decreases, in control situations when there was no exposure to stressors. They state that this could be explained by the fact that unlike HRV, which is regulated by the "central command", blood pressure is regulated peripherally and is influenced by local conditions in working muscles which could mask the changes of mental workloads. Thus, BP may not be as suitable as other physiological measurements for detecting subtle stress responses in real-time.

3.2.5.1. BP features. Systolic (SBP) and Diastolic (DBP) values have been used as features for analysing the BP [22]. Mean and standard deviation values, together with the number of peaks have been measured by Sharma et al. [51].

3.2.6. Skin Temperature (ST)

ST at constant room temperature may vary for different reasons, like fever, malnutrition, physical exertion and physiological changes [69]. If the other variables are controlled, effect of physiological changes could be appreciated. Physiological variations in the ST mainly come from localised changes in blood flow caused by vascular resistance or arterial blood pressure, which in turn are influenced by the ANS activity [70], suggesting that stress level changes ST. ST can be easily measured placing a temperature sensor in contact with the skin.

Skin Temperature has been measured in many stress and emotion detection researches [38,64,65,70]. However, not all of them agree on the effects that stress and emotions have on this parameter. Some of them affirm that finger temperature rises with stress [22]. In the experiment carried out by Palanisamy et al. [43], ST measured under the armpit increased in most of the subjects. Notwithstanding, others found out that finger temperature decreases under stress [40,71].

Skin temperature of facial features, such as the nose and forehead, could be an effective indicator in objectively evaluating human sensations such as stress and fatigue [72,73]. Nakayama et al. [74] found out in a research carried out with monkeys that a decrease in nasal ST is suffered when negative emotions arise. However, recent researches on facial thermal imaging suggest that facial temperature in some parts rises when feeling stressed [72,75].

Some other researchers simply state that ST does not provide much information about subjects' emotions [69]. This might be true when considering universal temperature patterns, but the reason for these disagreements may probably be that the temperature response hardly depends on each individual. Further research is needed to clarify this ambiguity.

3.2.6.1. ST features. Mean [65], minimum and maximum and the standard deviation [43,46] of the skin temperature have been used in the literature.

3.2.7. Electromyogram (EMG)

An Electromyogram measures the electrical activity of the muscles by using electrodes placed over the muscle of interest. As it is known that stress elevates muscle tone, many researches have been done to analyse the potential of EMG for measuring stress.

Stress has been found to provoke involuntary reactions on facial and Trapezius muscles [43]. In the study carried out by Wijsman et al. [76], it was verified that a significant increase in Trapezius muscle activity is suffered during mental stress. This increase in Trapezius muscle activity is translated into increased EMG amplitude and a decrease in the amount of gaps, i.e. short periods of relaxation. They also found out that low frequency contents increase significantly under stress situations, demonstrating that EMG signals give a useful information for detecting mental stress.

Wei [77] affirms that EMG is more effective than respiration signals for detecting stress levels. In this study, EMG and respiration measurements were done and a total of 37 features were extracted from these signals. LDA classifier was used for a 2-class classification problem, and the results showed that EMG signals provided a more relevant information than respiration signals, achieving 97.8% of accuracy discriminating relax and stress states with EMG, and 86.7% with respiration.

As most of the physiological measurements, obtaining an EMG can be obtrusive for certain situations. In order to make them more practical and realistic, Taelman et al. [78] developed a biofeedback EMG recording shirt for daily use.

3.2.7.1. EMG features. EMG statistics like the mean [50], median, standard deviation, Root Mean Square and minimum and maximum values are often used, as well as the range and the static, median and peak loads (10th, 50th and 90th percentile of rank ordered RMS values). Gaps have also the potential to measure stress levels, thus the average number of gaps per minute and the relative time with gaps (tGaps) have also been taken into account. Gaps are considered EMG values below the 5% RMS. Information about loads and gaps can be obtained from 1s segments of the reference contraction (Contraction signal). Mean and median frequency values and the first and second derivatives of the EMG in the temporal domain can also be found in the literature, as well as the number of maxima divided by the total number of signal values (maxRatio) and the number of minima divided by the total number of signal values (minRatio) [15,76,77].

3.2.8. Respiration

In 1973 researchers from the department of psychology of Peking University discovered that when the stress level changes, the speed and depth of respiration system also change [77]. Due to this finding, respiration has been measured in many stress-related researches [15,50,77,79] together with other physiological signals.

Respiration can be measured with a pneumotachometer (or pneumotachograph). Nevertheless, a device of this nature may be very intrusive and consequently, the possibility of estimating respiration rates from an ECG signal has already been analysed [80] with satisfying results.

Unfortunately, the literature suggests that respiration monitoring is not as worth as other physiological signals. Healey et al. [50] found out that contribution of respiration signals to stress detection was far from being as evident as EDA or HRV's contribution. Wei [77] also qualified respiration signals as less effective for stress classification than EMG signals.

3.2.8.1. Respiration features. Typical features obtained from respiration are the mean, variance, standard deviation, median, Root Mean Square, minimum and maximum values [15,70] as well as the range, the first and the second derivative, the maxRatio [77] and the respiration rate (rRate). Energy in four bands (0–0.1 Hz, 0.1–0.2 Hz, 0.2–0.3 Hz, 0.3–0.4 Hz) has also been considered [50].

3.2.9. Blood Volume Pulse (BVP)

Blood Volume Pulse is the measure of the volume of blood that passes over a photoplethysmographic (PPG) sensor with each pulse [81]. Photoplethysmography, consists of measuring blood volume in skin capillary beds in the finger, relying on the capability of blood for absorbing light.

BVP has not been used as frequently as other signals in stress detection researches. Zhai and Barreto [65] measured it together with other three physiological signals and a competent prediction method was developed. The biggest contribution of this signal in the literature is probably that it allows to measure information of HRV non-intrusively [40]. Chigira et al. [82] took advantage of this property, and described a photo-plethysmographic mouse to measure heart activity in office workers in a completely transparent way. More precisely, blood volume of fingers is measured using a near-IR light and a photo-detector, and enough IBI (Inter Beat Interval) precision is achieved to compute HRV features.

3.2.9.1. BVP features. The amplitude waveform of the BVP signal can be used directly [65], but it may be more useful to extract HR and HRV features or IBI features like the mean, standard deviation or the L/H ratio from it.

3.2.10. Pupil Diameter (PD), eye gaze and blinking

Pupil Diameter, eye gaze and blink rates can be measured with infrared eye tracking systems or with Image Processing techniques applied to visual spectrum images of the eyes.

Pupil dilations and constrictions are governed by the ANS [40]. Thus, PD exhibits changes under stress situations [46] and literature suggests that it can positively contribute to the problem posed herein.

Liao et al. [26] affirmed that pupils are dilated more often under stress situations. Later, Zhai and Barreto [65] used PD as stress inferring information, together with BVP, EDA and ST and the results indicated the validity of the chosen signals and features for a 2-class classification problem, i.e. to distinguish between stressed and not stressed people, as an accuracy of 90.10% was achieved.

Barreto et al. [83] have also carried out significant researches related to the PD activity under stress stimuli. They verified that the PD measured before and after the stress stimulus, show different statistics and that the mean of PD signal is significantly more relevant than the mean ST, mean BVP and the mean of BVP period for the identification of affective states [84].

Sakamoto et al. [85] measured PD variability in the same frequency bands as HRV, and they concluded that the LF/HF ratio of PD variability could effectively replace the LF/HF ratio of HRV, validating its use in stress recognition.

Recently, a work of Ren et al. [86] affirmed the high ability of PD features to discriminate between stress and relaxed situations. In fact, their results showed that PD outperforms EDA features. In their study, 42 individuals were subjected to an experiment where stress was induced by a Stroop test while their EDA and PD signals were being measured. A self-assessment test with 2 questions was answered by all the subjects to verify the stress eliciting method, and only those subjects who reported a higher stress response than a certain threshold were selected. T-test based labels were also computed to select relevant sections of the data. 3 features were extracted from each one of the signals. Five different classifiers were used to create the stress models, in which 4 out of five gave the best results using the questionnaire-based labels and only PD features, only one out of five using the combination of both EDA and PD features, and the worst in all the cases was achieved by using only the EDA based features. When t-test-based labels were used instead of the questionnaires, similar results were achieved: PD features outperformed all the others in 3 out of 5 cases, in the other two cases the combination of both gave the highest accuracies while there was no case in where the EDA outperformed PD. The highest accuracy of 88.71% was achieved with the Nanve Bayes algorithm, using only PD features and self-reported stress levels as ground truth.

3.2.10.1. PD features. Mean [65,86] of PD is probably the most used feature, but max value [86], standard deviation [51], percentage of large pupil dilation (PerLPD), pupil ratio variation (PRV) and Walsh coefficients ("Difference value between the first and the second Walsh coefficient after Walsh transform based on the PD signal during the onset of each Stroop segment" [86]) have also been chosen in some researches [26].

Whether eye gaze is a good predictor of stress levels has also been wondered by some researchers. It has been measured by Sharma et al. [51] and Liao et al. [26] for real-time stress detection when reading and working with a computer, respectively. In the latter, eye gaze spatial distribution was found to be positively correlated with stress levels. To be more precise, it was found that eyes focus more often on the screen and lay focused there more time under stressful situations. Eye gaze has also been measured for driving security purposes [87].

3.2.10.2. Eye gaze features. Eye pupils' coordinates have been measured for eye gaze tracking [26,87], as well as the Gaze Spatial Distribution (GazeDis) and the percentage of saccadic eye movement (PerSac) [26]. Sharma et al. [51] computed many features, namely the mean, standard deviation, the distance an eye covered, the number of forward and backward tracking fixations, proportion of the time the eye fixated on different regions of the computer screen and others.

Being aware of the effects of stress on the PD and eye gaze, it is natural to think that blinking may also vary under stress. Haak et al. [88] extracted blinking information from EEG signals while subjects were submitted to a simulated driving task. It was concluded that blink rate is directly related to the perceived stress, as it was evidenced each time a subject had a crash with a temporary increase in blink frequency. In the experiment carried out by Norzali et al. [72] too, it has been concluded that blink rate is highly correlated with mental stress. They found out that the blink rate under stress situation doubles, blinking 10 times per second in average before the stress stimulus, around 20 times under the stimulus and decreases at about 13 times per second after stimulus.

Nevertheless, others state the opposite idea. Liao et al. [26] affirmed that blink rate decreases under stressful situations.

3.2.10.3. Blinking features. Blink rate or blinking frequency is the most common blink-related feature, but average eye closure speed (AECS) has also been used [26].

3.2.11. Thermal Imaging (TI)

Several existing studies state that stress can be measured from thermal images due to the temperature changes suffered from stressed individuals [14,75,89]. Facial temperature can be easily measured using an Infrared camera, which is a completely unobtrusive method, making it interesting for office-place applications. In the past few years, this technique has been included in the set of stress measuring methods.

In 2009, Levine et al. [75] have used TI to analyse the activation of the corrugator muscle placed on the supraorbital area which may indicate mental stress. They concluded that progressive and sustained corrugator muscle warming was experienced by all the subjects under stress conditions. They also affirmed the possibility of detecting subtle changes using this method due to the lack of adipose tissue above the corrugator muscle, minimising the thermal inertia needed for provoking changes on the surface.

Norzali et al. [72] confirmed the previous information verifying that supraorbital temperature changes under stress situations, and went further finding out that blood flow under stress situations increased in periorbital and maxillary areas too.

A stress detection system using a combination of both thermal and visual spectrum (VS) facial data has also been tested by Sharma et al. [14]. Facial expressions were analysed in visual images while temperature changes have been detected in thermal images. Spatio-temporal features were extracted from recordings where individuals' faces were registered while watching stressed and not-stressed films. A classification accuracy of 85% of was exceeded using LBP-TOP (Local Binary Pattern – Three Orthogonal Planes) features for VS and LBP-TOP and HDTP (Histogram Dynamic Thermal Patterns) features for TI.

The promising results obtained with TI, have led other researches to analyse facial blood flow under stress situations with even more sophisticated methods. Recently, Chen et al. [90] have developed a stress detection system based on hyperspectral imaging, improving the TI technique for situations where big temperature changes or changes in subjects' sweating due to reasons other than stress may arise. The aim of using this technique was to detect the tissue oxygen saturation (StO2) on facial tissues, because the increase in facial blood-flow under stressful situations suggests that oxygen saturation may also vary. Results prompt the use of this method for stress detection because increased StO2 levels have been detected around the eye sockets and forehead areas, but further research is needed for verifying its viability in real-time and real-life situations.

3.2.11.1. TI features. Thermal images are used to extract temperature of different facial ROIs like the periorbital, supraorbital (corrugator area) [73], maxillary [72] and perinasal [89] areas. In some researches [14,60], temporal temperature patterns of 3×3 facial regions were extracted and mean, standard deviation, kurtosis, skewness, interquartile range, minimum and maximum values were computed from them.

3.2.12. Functional Magnetic Resonance Imaging (fMRI)

fMRI, is a technique for measuring brain activity. When the neural activity of a brain area increases, this area consumes more oxygen and to meet this increased demand, blood-flow increases to the active area. fMRI detects these changes in blood oxygenation and flow. Thus, fMRI can be used to produce activation maps showing which parts of the brain are involved in a particular mental process.

The number of research papers on brain functional activities associated with emotional stress using fMRI has increased because of its non-invasive nature and because it does not involve radiation, making it safer. Moreover, it is easy to use and it has a good spatial resolution.

The downside is that unlike EEG, fMRI does not provide a good temporal resolution. When brain function is analysed using EEG, both the temporal and spatial changes can be detected [53] and when analysing the stress response to a certain stimulus, good temporal resolution may be highly desirable. Furthermore, this method is restrictive by nature and it does not allow monitoring in the workplace [75].

Hayashi et al. [29] used fMRI technology so as to verify whether stress responses are evident in some brain regions, including the ones related to emotional and cognitive processing, while stimulating stressed and not stressed people with audio-visual contents. The results did not show differences on brain regions related to emotional processing, but did show less activity in cognitive processing brain regions on stressed people. They also found out that superior and inferior parietal gyrus was significantly more activated by pleasant and unpleasant stimuli in people not suffering from stress than those who were suffering from, suggesting that attention deficits may take place even on the early stages of stress.

3.2.12.1. fMRI features. When fMRI techniques are used, the available features are the activation or not of different brain areas under stress stimulus. Amygdala, Hippocampus, Superior Frontal gyrus (SFG), Inferior Frontal gyrus (IFG), Inferior Parietal gyrus (IPG), Superior Parietal gyrus (SPG) and Superior Temporal gyrus (STG) [29] are the typical parts involved in the stress response analysis.

3.2.13. Summary

Table 1 summarises the aforementioned physiological signals and features present in the literature.

As it has been seen in this section, there are many physiological signals that have been used in stress detection and some of them have shown to provide reliable information about peoples' real-time stress levels. Unfortunately, the drawback of most of them is that extra equipment is necessary for the measurements, becoming an obtrusive method for the real-life. Even if some researches [27] are focused on creating wearable physiological measuring systems to make them more transparent, the user is forced to wear continuously those equipments, which remains being unobtrusive and even not affordable for some people. Solutions that aim at overcoming these drawbacks are being developed and are discussed in the Section 5.4.

3.3. Behavioural responses

Behaviour regards expectations of how a person or a group of people will behave in a given situation based on established protocols, rules of conduct or accepted social practices [22].

Stress affects in individuals' behaviour. Some of the induced changes are well-known, for example, being much more irritated or angry, but these are not easily measurable. Other possible behavioural changes have been investigated, for example, by analysing people's interaction with technological devices in order to verify their relationship with stress and to create a reliable way to measure it. The advantage of measuring behavioural responses is that unlike physiological measurements, they can normally be done in a totally unobtrusive way and in some cases, without the need of expensive extra equipment.

3.3.1. Keystroke and mouse dynamics

Keystroke dynamics is the study of the unique characteristics that are present in an individual's typing rhythm when using a keyboard or keypad [91]. The same way, mouse dynamics are affected by the subject's characteristics when moving it or clicking on its buttons.

Keystroke and mouse dynamics have been widely analysed in the security area for authentication of people [92,93] and for emotion recognition [94] as Kolakowska et al. explain in their recently published review [95]. Stress detection, although fewer, has also been the objective of some researches based on keystroke and mouse dynamics.

In 2003, Zimmermann et al. [31] first mentioned the possibility of using mouse and keyboard dynamics information to measure the affective state of the user. Thenceforth, many other researchers have tried to implement a method based on different features extracted from these devices.

One of the biggest advantages of using a keyboard and a mouse for this purpose is that the developed technique is not intrusive and there is no need of any special hardware. Vizer et al. [36] highlighted other advantages like allowing to monitor information continuously leading to the possibility of an early detection and permitting to easily extract baseline data. Moreover, the article states that this kind of systems can be introduced in the users' everyday life without the need to change their habits.

Peoples' writing patterns are considered to be stable enough for security applications, but small variations which have been attributed to stress and other situational factors on these patterns have been detected. Some researchers, as, for example, Hernandez et al. [37], affirm that relevant information about the affective and cognitive state of the user can be provided by keyboard dynamics. In their study, they used a pressure sensitive keyboard and a capacitive sensing mouse in order to detect stress levels in users. Self-reports and physiological signals were used as reliable assessment techniques. The results showed that 79% of the participants increased significantly the typing pressure and that the 75% had more contact with the mouse under stress. This may be inconsistent with other researches [26] that affirm that the mouse button is clicked harder when stress is decreasing. Surprisingly, at odds with other studies, no significant differences were found in terms of the amount of characters introduced, task duration or typing speed between the stressed and relaxed conditions.

Other authors, disagree that keyboard dynamics provide relevant affective and cognitive information. Alhothali [96] stated that typing speed, key latency and key duration are only weakly correlated to emotional changes. Nevertheless, some researches [97] have already gone a step further accepting the reliability of behavioural biometrics based on keyboard and mouse usage patterns to assess stress levels and using it to extract personality traits.

3.3.1.1. Keystroke and mouse dynamics' features. The most frequently extracted features from the keystroke dynamics are dwell time, which is the time a key is pressed, and the average dwell time, duration between keystrokes (KeysUp) and their average, time between two consecutive keys are down (tDown), pause rate, typing speed, number of key press events (nKeys), duration of digraphs and trigraphs, number of events in the key events combination (nEvents) and frequency of using specific keys such as backspace or the space-bar [98,99]. Key pressure has also been measured in some researches [37].

Mouse dynamics are typically characterised by mouse horizontal and vertical speeds (v), acceleration (a), frequency of movement, stillness, x and y coordinates of the mouse, overall distance and the direction. Average speed against the distance travelled (vDistance) and average speed against the movement direction (vDirection) have been measured too, as well as the number of

Table 1
Physiological features used in the literature.

Signal	Ref.	Feature	Parameters
ECG	[27,43–46,48–55],	μ, SD, P and E	
		HR	μ, min, max
		HRV	Temporal & geometric: μ, SDNN, SDANN, RMSSD, pnn50, SDSD, HRV TI, TINN, Kurt., Skew., 2nd, 3rd and 4th-order cum. Frequential: LF/HF, HF/All, (LF + MF)/HF, ULF, VLF, LF, HF and total P. Non-linear: T, E, C, SD1 & SD2 of Poincaré Plot, Long-term & Short-term fluctuation slope in DFA, min & max lines in RP, Recurrence Rate, Determinism, Correlation Dimension
EEG	[53,57,59–62]	μ, Fractal dim., HOC, Hjorth params., spatial-spectral features	
		ERP components	μ
		Spectrum	α, β, δ and θ bands' mean P and mean P ratios
		LLE	μ and SD
		KDE features	μ and σ^2
EDA	[21,30,40,45,50,51,65–67]	μ, SD, min, max, RMS, Kurtosis, Skewness, DiffAvg, DiffMax, DiffMin, MaxPos, MinPos, ZC	
		Orienting responses	O, P, D, M, no. of P, P height, avg. M and D, μ, latency, tRise, tRecovery, $\sum$ M, $\sum$ D, Aq, Dq, areaResp, areaRise
BP	[22]	μ, SD, no. of peaks, SBP, DBP	
ST	[43,46,65]	μ, min, max, SD	
EMG	[15,50,76,77]	μ, median, SD, min, max, range, minRatio, maxRatio, Diff., Diff2	
		Contraction signal	μ, static, median and peak loads, Gaps/min, tGaps
		Spectrum	μ frequency, Median frequency
Resp.	[15,50,70,77]	μ, SD, Diff., Diff2, median, min, max, range, maxRatio, rRate	
		Spectrum	Power of 0–0.1 Hz, 0.1–0.2 Hz, 0.2–0.3 Hz and 0.3–0.4 Hz bands
BVP	[65]	Amplitude	
		IBI	L/H, μ, SD
		HR	See ECG
		HRV	See ECG
PD	[26,51,65,86,87]	μ, max, SD, PerLPD, PRV, Walsh coeffs.	
Eye gaze		Eye position	GazeDis, PerSac μ, SD, distance, no. of fwd. and bw. tracking fixations, and tFixed
Blinks	[26]	Blink frequency, AECS	
TI	[14,73,72,89]	Facial (3 ROIs) temperature	
		Temporal facial T° patterns	μ, SD, kurtosis, skewness, interquartile range, min and max
fMRI	[29]	ROIs: Amygdala, Hippoc., SFG, IFG, IPG, SPG and STG	Activation of the ROIs

clicks including left, right and both buttons (nClicks), absolute sum of angles and mouse wheel movements (nWheel) [37,98,99].

Covered distance between two button press events (DPP), distance the cursor has been moved between a button press and the following button release event (DPR), between two button release events (DRR) and between a button release and the following button press events (DRP) have been computed [98], as well as the Euclidean distances in the previous cases (EuDPP, EuDPR, EuDRR, EuDRP), the difference between the covered and the Euclidean distance between the events described before (DifDPP, DifDPR, DifDRR, DifDRP) and the times elapsed between the mentioned events (tDPP, tDPR, tDRR, tDRP).

3.3.2. Posture

It has been proven that posture is a good indicator about the feelings of the worker towards the tasks they are carrying out [100]. Thus, individuals' postural behaviour may also provide important information about stress levels.

Anrich et al. [101] have tried to verify this hypothesis analysing the changes in the posture of office workers using a pressure distribution measuring system installed in their chairs. The spectra of the norm of the centre of pressure (CoP) was used as postural feature. 28 men were stressed using the MIST [102] and it has been verified that the amount of fast movement increases during stress tests compared to control tests, and that the spectra of the CoP obtained in the two tests also show differences. Using spectral information, 73.75% of accuracy was achieved when separating stress situations from cognitive load, suggesting that postural behaviour contains information related to stress levels.

Others [30] have analysed the posture using visual techniques. Specifically, a Kinect has been used for detecting the interest levels of the office workers. Using techniques such as depth information and skeletal tracking, the inclination of the person and consequently an indicator of the workers' motivation was deduced.

3.3.2.1. Posture features. To analyse subjects' postural behaviour, direction of lean has been evaluated [30] measuring the gradient from front-to-back and from side-to-side. The mean of several spectral bands of the norm of the centre of pressure (CoP) measured on a chair were computed in [101].

3.3.3. Facial expressions

Automatic recognition of facial expressions has been the subject of many researches [87,103,104]. They can be estimated with computer vision techniques [30] or by means of a facial Electromyogram (EMG). The latter can provide better time resolution and greater sensitivity when measuring the weakest responses of the facial muscles, but it is also much more obtrusive than the former for real life applications [105]. Furthermore, EMG can sometimes be less selective than desirable because the electrical activity created by a muscle can be extended to the adjacent areas, and moreover, activities that are not related to emotions, such as speaking, can generate confusing EMG activity. Thus, most of stress related researches using facial expressions have used visual techniques.

Dinges et al. [103] created an Optical Computer Recognition (OCR) technique to detect facial expressions related to stress induced by workload. Self-reports, salivary cortisol measures and HR signals were used as ground truth. A 3D deformable mask was created to detect changes in eyebrows, mouth and lips (including asymmetry, which is especially useful for stress recognition) and HMM was used to detect facial stress patterns, achieving classification results of between 75–88% when discriminating high and low stress levels and thus, validating the potential of eyebrow and mouth movements' measurement for this purpose.

McDuff et al. [30] analysed facial expressions together with head movements using a Webcam, in this case for valence detection, and concluded that they are a good source of information. This suggests that they can be equally valid for stress recognition. In a recent work [106], unlike in most of stress detection researches, a mathematical stress model was created instead of considering the main objective as a classification problem. Instantaneous facial expressions were analysed from images, creating an emotional percentage mixture model and relating it to stress levels. Moreover, the seven basic emotions, without any image for reference, were also related to stress, and finally, the equation for evaluating stress quantitatively from facial expressions was estimated. Unfortunately, no information about its performance was provided.

3.3.3.1. Facial expressions features. Mean smile intensity, mean eyebrow activity and mean mouth activity are the typical facial features measured [30,103]. Some researches [87] have measured these features placing 22 points of interest (POIs) around the eyes, nose, mouth and eyebrows.

3.3.4. Speech analysis

Many researchers agree with the fact that stress changes human vocal production [107–109]. More precisely, it has been found out that under stress situations, changes in pitch (fundamental frequency) and in the speaking rate are usual, together with variations in features related to the energy and spectral characteristics of the glottal pulse [108]. Speech analysis has caused interest principally because it can be easily measured in a completely unobtrusive way.

Nevertheless, voice-based stress analysis can be ineffective both in quiet and noisy spaces [110], due to the lack of speech recordings and to the excessive noise, respectively. Most of the research done in stress recognition from voice, has been carried out in laboratories or in quiet environments, but there are exceptions, such as the research carried out by Lu et al. [108], where stress detection both in indoor and outdoor acoustic environments was executed, using mobile phones. An accuracy of 82.9% indoors and of 77.9% outdoors was achieved.

Demenko et al. [111] analysed call-centre recordings, including stress and no-stress speech. They achieved 84% accuracy distinguishing between the two classes, using LDA classifier and 9 features extracted from amplitude and pitch information.

In the laboratory experiment carried out by Kurniawan et al. [21], speech and EDA were measured and used to create a universal stress model and an inter-individual stress model, both with independent information given by each signal and combining the two of them. Three two-class classification problems were considered: recovery vs. workload, recovery vs. heavy workload and light workload vs. heavy workload. Results showed that the selected speech features (Mel Frequency Cepstral Coefficients and pitch) were more efficient for stress detection than the selected EDA features. Furthermore, the combination of both types of signals didn't show any improvement and as expected, the inter-individual model outperformed the universal model. Thus, the best result for the most difficult case (distinguishing light and heavy workload) was achieved using the inter-individual model with the SVM classifier and speech features: 92.6% of accuracy. This result suggests that effectively, stress detection can be done by means of speech features when the subject is placed in an environment with good acoustic conditions.

3.3.4.1. Speech features. Pitch is the most frequently extracted feature from speech in stress detection. It has been found that mean value, standard deviation and range of pitch increase under stress while pitch jitter decreases [108]. Minimum, maximum, median and first derivation of pitch are also used by some researchers [21,111]. As spectral centroid goes up under stress and energy is concentrated in higher frequency bands, high frequency bands' (above 500 Hz) energy is also considered. Speaking rate also increases, as well as voice intensity. Intensity features like the mean, range and variability can be used in certain environments [108]. Amplitude-based features were used by Demenko et al. [111], precisely, the perturbation quotient (sAPQ), the degree of subharmonic segments (DSH), the noise to harmonic ratio (NHR) and the degree of voiceless (DUV). However, pitch and speaking rate features frequently the most suitable ones, because they can work well even in noisy environments.

Smoothed energy, voiced and unvoiced speech, Mel Frequency Cepstral Coefficients (MFCC) and Relative Spectral Transform – Perceptual Linear Perception (RASTA-PLP) [21,107] have also been computed in some cases. Teager Energy Operator based non-linear transformation (TEO-CB-AutoEnv) has also been applied to the signal for better computing pitch and harmonic related parameters [108].

3.3.5. Mobile phone usage

Nowadays, a huge amount of information related to users' behaviour can be extracted from Smartphones. Call logs, SMS, e-mails, internet browsing, app's usage, location data and many other knowledge can be easily obtained without the user even noticing it. Recently, research on stress detection has evaluated the possibility of taking advantage of this unobtrusive information collecting method.

Muaremi et al. [112] used iOS Smartphone data collected during the day and HRV data registered when sleeping, to classify people in low, medium and high work-related stress groups. Feature selection techniques were used to result in a seven features' collection where 4 belonged to HRV and 3 to Smartphone data, suggesting that HRV features were more important than the extracted Smartphone features in this case. The best results were achieved in the user-specific model case, with an accuracy of 55% with only Smartphone data, 59% with only HRV data and 61% with the combination of both. This classification results also show that the selected HRV features were better than the Smartphone features selected for the stated classification problem. However, Smartphone derived features worked better than chance (which in this case was 33%) affirming that they could also provide some information to the stress recognition methodology.

In the research carried out by Sano et al. [66], skin conductance, 3D accelerometer data and mobile phone usage data were collected in order to assess users' stress levels. Calls, SMS, location, communication aspects and screen on/off events were monitored as phone usage data and 351 features were extracted from this information. Other 240 features were extracted from surveys and accelerometer and skin conductance data. Correlation of both physiological data and mobile usage data with PSS was proven. Results suggested that under high levels of stress, the sent SMS percentage among all sent and received SMS decreases, together with the percentage of the length of all sent and received SMS. They also indicated that screen on/off patterns change, decreasing the "on" time, showing less variation of this time between 6 pm and 9 pm and turning on the screen earlier in the day. Thus, it has been proven that mobile usage patterns change under stress, and an accuracy of over 75% in high and low stress detection was achieved.

3.3.5.1. Mobile phone usage features. The number of calls (nCalls), the sum of all call duration (tCalls), mean, variance and median of call duration, and the ratio between incoming and outgoing calls have been obtained from mobile phones [112]. The relative changes of the number of contacts, phone numbers, and e-mail addresses have also been measured. Battery usage is also used as a stress inferring feature, calculating the time the battery is not charging (tNotCharging) and the time the battery is charging (tCharging).

Mean, SD and median of the time of each SMS message (tSMS), mean, SD and median of length for all SMS messages (lSMS), the total number of SMS messages (nSMS), the ratio between received and sent SMS are also measured as well as the mean, SD and median of unanswered calls and the total number of individuals with whom a participant interacted through calls (ncPeople) or SMS (nsPeople) [66].

Screen features are also taken into account: Mean, SD and median of the time of each screen on (tScreenOn) and the number of times screen has gone on (nScreenOn) have been studied [66].

3.3.6. Computer exposure

It is natural to think that computer exposure of workers changes under high stress levels because high workload is one of the reasons for individuals to be stressed, and this could lead workers to spend more time in front of the computer. Eijckelhof et al. [11] have investigated neither stress levels affect the overall human–computer interactions within a day, i.e. computer exposure times and breaks' frequency and lengths, using a specific software for this purpose. They affirm that workers suffering from individually oriented stressors, i.e. overcommitment and high perceived stress levels, spend more time in front of the computer during the day, while the workday itself is not extended. In addition, they suggest that these stressors do not affect on their break patterns. Besides, they concluded that workers with high levels of organisationally oriented stressors, i.e. effort and reward, tended to have fewer short (30 s–5 min long) computer breaks and slightly longer breaks (more than 15 min).

3.3.6.1. Computer exposure features. In this study, the mean of total duration of computer interaction for each workday and the mean of the number of short (30 s–5 min), medium (5 min–15 min) and long (>15 min) breaks per workday were extracted from the computer interaction information. The mean duration of total workdays was also computed.

3.3.7. Smart environments

Much research work has been done in the smart environments area related to people's behaviour pattern detection [113,114]. Some of these researches are placed in office environments [115–118]. Nevertheless, many of these researches have been oriented to energy efficiency and they have hardly been used for stress recognition purposes.

Suryadevara et al. [119] carried the emotion detection problem, including stress, to a Smart House, suggesting that an initial change in regular daily activities can mean changes in health. They created a two part monitoring system, which included on one hand, physiological information obtained from heart rate, skin temperature and skin conductance signals in order to determine the emotion of the person. On the other hand, a smart house with wireless sensors to monitor house appliances' usage in order to detect abnormal behaviours. The idea of analysing information extracted from such different sources can be very interesting, on one hand because of their complementarity, and on the other hand because of their non-invasive and privacy respecting nature. Unfortunately, both parts of the system as described in the article were completely independent, and a method for integrating their results and to find correlations was not even mentioned.

3.3.7.1. Smart environments' features. In this study, activities were deduced from the sensor activation information, and at the same time, the duration of devices' use and inactivity times were computed, enabling this way the computation of the wellness function.

3.3.8. Text linguistics

The way a subject writes can vary depending on his stress levels. On one hand, some pressure can enhance the writing abilities of a person, making writings of better quality, using a more diverse lexicon, etc. On the other hand, mood can be directly reflected on the text being written, especially, in free texts. Therefore, analysing text linguistics can be an added value for a stress recognition system.

Currently, there exist many tools that allow to automatically analyse linguistic features, as, for example, LIWC [120], Harvard General Inquirer (GI) [121], Semantria [122], SentiStrength [123], Synesketch [124], which can be used both measuring writing performance in users by means of lexical diversity measures, or directly analysing the "feelings" of the text, which is their main purpose. These tools count the word-type rate (such as the self-reference rate, or article rate), as well as their polarity, i.e. their positivity or negativity, and strength (the degree in which they are positive or negative) [120,123]. There is a whole scientific branch dedicated to the sentiment analysis of texts, which could be considered the neighbour of stress detection. Sentiment Analysis (also called opinion mining, subjectivity, analysis of stance, etc.) aims at finding a polarity and strength value for any text, analysing it word by word, following some pre-established dictionaries and their corresponding sentiment classification. We refer the user to the review of Taboada et al. [125] for further information.

Whereas sentiment analysis techniques have been widely used for analysing, for example, depressive moods [126,127], only a few studies have focused on inferring stress levels from texts: this is the case of Saleem et al. [128] and Vizer et al. [36]. The former used this technology to analyse online forum posts and detect user stress levels from them. GI and LIWC tools were used for sentiment analysis, but many other features, like pronoun count, punctuation count or features more specialised on forums, were also extracted from the texts. The different feature combinations were tested with an SVM classifier and Markov Logic Networks (MLN) giving promising results. Free text analysis was done by Vizer et al. and timing, keystroke and linguistic features were analysed in order to distinguish between physical stress, cognitive stress and no stress situations. An improvement on lexical performance under both types of stress was found, reducing the number of mistakes, increasing lexical and content diversity and decreasing pause lengths. They found out the possibility of distinguishing both types of stress affirming that physical stress affects on linguistic features while the cognitive stress affects more on keystroke. They achieved classification rates of 62.5% for physical stress and 75% for cognitive stress.

3.3.8.1. Linguistic features. Many linguistic features extracted from a free text have been considered [36], in order to measure the writing performance of the subjects. The features included lexical and content diversity, that measure the rate of unique words and content words, noun and verb rates, average word length, function word rate where determiners, conjunctions, prepositions, pronouns, auxiliary verbs, modals and quantifiers are included, conjunction rate, cognition operation rate (considering cognition words the ones that express cognitive operations such as thinking), emotive word rate as well as modifier rate where all adjectives and adverbs are considered, adjective rate, intensity word rate (where words like "greatly" or "seldom" are taken into account), negative and positive affect rates, sensory information rate where words expressing sounds, smells, and physical sensations are included, passive tense rate, third person pronoun rate, modal verb rate, negation rate where all kinds of negative words are considered, first person plural pronoun rate, self-reference rate, generalising term rate where words referring to a class of people and objects like "everyone" or "none" are counted and finally, average sentence length. Polarity and strength of the text have also been considered [128].

3.3.9. Summary

Table 2 shows a summary of the behavioural measurements and features used in the state of the art.

Behavioural measurements for stress recognition are much less frequent than the physiological ones in the state of the art. They have not probably been still enough studied, and thus, stress detection results in general are not as accurate as with physiological methods. Even so, some of them look very promising, on one hand because of their results and on the other hand, because they do not require any extra equipment. Precisely, this is the biggest advantage of the behavioural measurements: in many cases, no extra equipment is needed, and when it is necessary, it is unobtrusive to the user as no contact nor different behaviours or habits are needed, being totally transparent methods. Furthermore, this leads to a decrease in the developed system's cost.

3.4. Contextual information

User context is defined as one or a group of parameters, which deliver information about the state of a user at a certain point in time [16]. The place, the time and the ambient factors where the subject is may affect the stress response, thus, measuring these parameters could help inferring the subjects' stress levels.

3.4.1. Calendar events

Meetings a worker is attending, people with whom he is interacting or tasks he is developing can be registered as calendar events and can give information about an individual's workload and stressors. Some researches have taken into account the vast amount of information that calendar events can provide about an individual's stress level.

In 2012, AffectAura [30], which is an emotion tracking system and a reflective tool for office workers, was created combining audio, visual, physiological and contextual data. Contextual data included calendar events and GPS information, along with file activity. The study concludes that registered calendar events were very useful for people in recalling their mood of a certain moment in the past, thus, calendar events could help tracking the emotions and stress over the time. Unfortunately, AffectAura did not offer the possibility of creating patterns and detecting abnormalities automatically.

Later, calendar events have been analysed along with some physiological (skin temperature, skin conductivity), physical (3D acceleration) and some other contextual information (lighting and ambient temperature) [38]. A modified Self-Assessment Manikin test was used for collecting subjective information about the user's feelings in relation to each calendar event. A stress level monitoring and memorising environment was created and tested for 4 weeks, resulting in a useful tool for recognising stressors and for tracking stress levels within the time. The same way as in AffectAura [30], the registered information had to be evaluated by the user or by an expert manually.

Much more research is needed in order to develop a stress measuring methodology using calendar information. These researches can help in creating stress patterns for each individual, recognising each individual's stressors in order to use such information in stress recognition applications.

3.4.1.1. Calendar features. Number of events, total time spent on events, mean value of event duration, and the mean size of notes [112] and valence, arousal, energy and dominance level obtained by a self assessment questionnaire of each calendar event [38] is taken into account from calendar data.

3.4.2. Location and ambience

Location and ambiance can also affect in our stress levels. For example, the simple fact of being in the workplace can make some people feel more stressed than when they are at home. Therefore, tracking location could also help to recognise stress. Taking this into account, location (mobile phone's location) of the user, together with activity (physical activity, call status, ringer status, and Keyboard and mouse dynamics' features) and ambience (ambient audio features) information was collected using a smart phone and a personal computer in a research [16]. To assess stress levels', a HMM which models seven levels of stress was used.

They stated that the results looked promising but unfortunately quantified results are not available in the paper.

3.4.2.1. Location and ambience features. The total distance travelled during the day and the number of locations visited were calculated using GPS in the experiment of Muaremi et al. [112], where locations were derived using the DBSCAN [129] algorithm. Mean, SD and median of radius and distance have also been measured [66]. In a research[16], location was used as a three-value parameter, distinguishing between home, work and unknown places. Ambient sound was also measured to differentiate silent, low-volume and high-volume ambiences.

3.4.3. Summary

Table 3 summarises the contextual measurements and the features that are present in the state of the art.

Contextual data cannot measure peoples' stress response. Context does not vary with users' stress levels, but it can affect on people's reactions. Thus, contextual measurements cannot be interpreted the same way as the aforementioned modalities' measurements, but they can provide information about personalised stressors after a learning stage, or about the probability of a user to be highly stressed, for example, based on calendar events. Including this kind of information could help improving the developed system's accuracy in a totally unobtrusive and low-cost way, because as in the case of behavioural measurements, expensive equipment is not needed.

Table 2
Behavioural features used in the literature.

Signal	Ref.	Feature	Parameters
Keyboard use	[37,98,99]	Keystroke	KeysUp, avg. KeysUp, dwell time, avg. dwell time, nKeys, typing speed, use of particular keys, pause rate, tDown, duration of the digraph/trigraph and nEvents
		Pressure	
Mouse use	[22,37,98,99]	Movement	Coordinates, overall distance, stillness, horizontal v, vertical v, tangential v, tangential a, tangential jerk, angular v, vDistance and vDirection
		Clicks	nClicks, menu and toolbar clicks, DPP, DPR, DRR, DRP, EuDPP, EuDPR, EuDRR, EuDRP, DifDPP, DifDPR, DifDRR, DifDRP, tDPP, tDPR, tDRR, tDRP
		Wheel use	nWheel
Posture	[30,101]	CoP	μ of several frequency bands
		Lean	Gradient front-to-back, gradient side-to-side
Facial Expressions	[30,103]	AAM or POIs	Mean smile intensity, Mean eyebrow activity, Mean mouth activity
Speech	[21,107,108,111]	Speech waveform	Speaking rate, voiced and unvoiced speech
		Intensity	μ, range and variability
		Pitch (f0)	μ, min, max, SD, median, jitter, range, 1st derivation
		Spectrum	Spectral centroid, smoothed E, E > 500 Hz
		MFCC (Cepstrum)	μ, σ^2, min, max of the first 12 cepstral, δ and δ-δ coefficients
		TEO-CB-AutoEnv feature	Pitch and harmonic related params.
		RASTA-PLP	μ, σ^2,min, max
Smartphone use	[66,112]	Calls	nCalls, tCalls, μ, σ^2 and median of call duration, incoming/outgoing calls, μ, SD and median of unanswered calls and ncPeople
		SMS	μ, SD and median of tSMS, μ, SD and median of lSMS, nSMS, received/sent SMS, nsPeople
		Screen use	μ, SD and median of tScreenOn and nScreenOn
		Contacts list	Changes of the no. of contacts, phone numbers, and e-mail addresses
		Battery use	tNotCharging/tCharging
Computer exposure	[11]	Computer interaction	Total interaction, short, medium and long breaks per workday
		Log on/off	Duration of workday
Smart home sensor events	[119]	Activity	
		Use/inactivity times	Wellness function
Text linguistics	[36,128]	Free text	Lexical & content diversity, noun rate & verb rate, average word length, function word rate, conjunction rate, cognition operation rate, emotive word rate, modifier rate, adjective rate, intensity word rate, positive and negative affect rate, sensory information rate, passive tense rate, other reference rate, modal verb rate, negation rate, group reference rate, self-reference rate, generalising term rate, average sentence length, polarity, strength

Table 3
Context features used in the literature.

Signal	Ref.	Feature	Parameters
Calendar	[38,112]	Subjective feelings about events	Valence, arousal, energy and dominance level
		Times and attendees of meetings	Peoples' interactions
		Events	No. of events, total events time, mean event duration
GPS	[66,112]	Latitude and longitude	Distance/day, μ, SD and median of radius and distance, current location: home, work or unknown
		Location	No. of locations
Ambient sound	[16]	Volume	
File activity	[30]	File instances	No. of activities, no. of unique activities

3.5. Multimodal techniques

As it has been seen in the previous sections, information about a phenomenon, in this case stress, can be acquired using different types of instruments and measurement techniques [130]. Each acquisition framework is called a modality, and thereby the setup of a framework making use of different modalities is called multimodal. Lahat et al. [130] affirm that multimodality provides redundancy to the data set, which can help in resolving otherwise ill-posed problems.

In the context of stress detection, Liao et al. [26] affirm that "the effectiveness of multiple-modality information fusion is demonstrated by the increasing accuracy of inferred stress with the number of source evidences". They also state that "some physical symptoms such as fast heart rate and rapid breathing are not unique to stress" so information coming from different modalities could help discriminating stress and no-stress situations. Carneiro et al. [28] affirm that for a sufficiently precise and accurate measurement of stress, a multimodal approach should be considered.

Many stress recognition researches have taken advantage of this multimodal nature of stress and have combined very different information. Examples of this are the research of Healey et al. [50] and Wijsman et al. [15] who combined several physiological features coming from EDA, ECG, EMG and respiration, or Zhai and Barreto [65] who used PD, BVP, EDA and ST for measuring stress levels. Nonetheless, most of them have only made use of physiological data. Much less examples can be found that have mixed data coming from different domains, i.e. psychological, physiological, behavioural or context modalities.

One of the few examples could be the work of Liao et al. [26], who affirmed that their research was the first one combining measurements of the three principal modalities. They combined EDA, HR, ST, PD, eye gaze, blink dynamics and facial expressions as physiological measurements, head movements, mouse clicks and pressure as behavioural measurements as well as errors and response times of mathematical and audio exercises as performance evaluators.

Kaklauskas et al. [22] created a computer-based advisory system, called "The Web-based Biometric Computer Mouse Advisory System to Analyze a User's Emotions and Work Productivity" to detect emotions, including stress, using physiological (heart rate, systolic and diastolic blood pressures, user's hand temperature and humidity, skin conductance) and behavioural measurements (mouse touch intensity, clicks and movements, hand–holding time) and a validating system based on a psychological self-assessment questionnaire.

In the research of Kocielnik et al. [38], a continuous stress level monitoring system was proposed using physiological (EDA, ST), behavioural (3D acceleration) and contextual (ambient temperature, lightings and calendar events) information, together with subjective information extracted from questionnaires.

Okada et al. [27] have also made use of accelerometer data in combination of physiological signals in order to identify the actions being carried out by the monitored subjects and by the way, remove movement artifacts.

The lack of literature in stress detection using multimodal data of different domains may be due to several reasons, including, the problems that may pose the integration of such diverse data and the multidisciplinary approach that this kind of research implies. Nevertheless, this area is gaining interest and the results of the aforementioned researches and the advantages of multimodality in general suggest that researching in a multimodal system for stress detection could improve the state of the art.

Table 4 shows the best stress detection accuracies achieved in the state of the art. It can be appreciated that SVM classifier was used in 5 out of the 15 best results, suggesting the high potential of this classifier. LDA, is probably one of the most simple classification algorithms, but its satisfactory performance can be verified since 4 out of the 15 best results were achieved with this classifier. Fuzzy classifier is present only once, but it is the one who has achieved the best classification result, nearly the 100%. Its low frequency in this ranking is probably because it has not been sufficiently tested on stress and emotion detection areas.

Regarding the signals and features that can be found in the ranking, EDA and ECG are present in four studies each, verifying their potential for stress recognition purposes. ECG is exploited using the HRV features in the vast majority of cases, and in EDA's case, the mean value and the orienting responses are the most frequent features.

It is remarkable that all the signals that are present in this ranking of the best stress detection accuracies are physiological measurements. Neither behavioural, performance nor contextual measurements have been used resulting in as high classification results as with physiological signals. This is logical because physiological measurements have been much more considered since many years ago in stress detection, but also in many other kinds of researches and thus, their handling is much better achieved. However, this does not mean that other kind of measurements are not able to provide as good classification accuracies as the ones gotten by physiological measurements, but that much more work is still to be done. State of the art shows that behavioural, performance and contextual measurements have also the potential to distinguish between stress and no stress situations and a detection method based on these alternative techniques could improve the actual detection systems as they can be completely unobtrusive and transparent for the user.

4. Psychological stress elicitation

In order to carry out stress-related researches, it is necessary to provoke the stress response on the desired subject at the required moment. For this purpose, many different stress elicitation methods have been validated. Probably the most frequently used method has been the Stroop Color-Word Interference Test, followed by mental arithmetic tasks. Both methods have been frequently studied [43]. Car driving is also considered a stress eliciting task [50], as well as watching films with stressful content [14,131], or playing computer games. In a research [77], speed and difficulty of the game "Tetris" have been varied in order to provoke stress and calm reactions alternately on subjects. Public speaking tasks [79,132] and the Cold pressor test [133] have also been used. Finally, Dedovic et al. [102] have tested and validated fMRI as a stress eliciting method.

5. Framework approach and methodological issues

The development of such a continuous, unobtrusive and automatic early stress detection system, implies difficulties other than choosing the most appropriate and significant signals and features for it. As in any application that involves the use of big amounts of data, the steps followed to collect and store or process this data are of high relevance, in order to ensure the quality and the reliability of the system.

A possible solution for the automatic stress detection system is shown in the Fig. 3. Such a system requires data to be collected, transmitted, preprocessed, reduced, merged and used for automatically making the final decision. Nonetheless, all these steps imply several difficulties and therefore, they may vary both in the order in which they are performed and in the way they are implemented in order to overcome the methodological issues.

5.1. Data collection and quality

The first step of such a system is the *data collection*, which has to be meticulously carried out in order to ensure its quality. For data to be of high quality, it must be "accurate, complete, relevant, timely, sufficiently detailed, appropriately represented, and must retain sufficient contextual information to support decision making" [134]. Nowadays' physiological monitoring devices, such as the BIOPAC System [135] or the FlexComp System [136], allow high quality data acquisition. Nonetheless, some varying factors can affect and thus, they have to be taken into account.

The incorrect placement of electrodes would derive in meaningless measurements, so in order to avoid ambiguities, standards for the correct measurement of physiological data have been defined and are internationally used. It is the case of the International 10-20 EEG System [137] or the standard 12-lead ECG. For sensors that do not have any standards defined, trials must be done to verify the best placement. It has been verified that different body placement of the sensors result in different signal patterns and classification accuracies [138]. Sensor placement is also crucial to the quality of the behavioural signals' recording in AI environments [139].

Sampling frequency of the data must also be adequate to the signal being collected, in order to establish a compromise between the amount of data to be treated and the quality obtained from them. Khusainov et al. [140] affirmed that for ADL (Activities of

Table 4
Best classification results of the state of the art according to accuracy.

	Acc. (%)	Prec. (%)	Rec. (%)	Ref.	Signal	Features	Parameters	Class.
1	98.45	97.5	99.5	[45]	EDA	μ, σ^2		Fuzzy logic
					ECG	HR	μ, σ^2	
2	98	–	96[a]	[60]	Thermal images	Temporal facial T° patterns	μ, SD, kurtosis, skewness, interquartile range, min and max	SVM
					EEG	Hjorth params., fractal dim.		
						Spectrum	α, β, δ and θ bands' mean P	
3	97.3	97.4	97.4	[50]	ECG	HRV	LF/HF, (LF + MF)/HF	LDA
					EMG	μ		
					EDA	Orienting responses	Onset, peak, duration, magnitude, total no. of peaks, sum of magnitudes, sum of response durations, areaResp	
					Resp.	Spectrum	Power of 0–0.1 Hz, 0.1–0.2 Hz, 0.2–0.3 Hz and 0.3–0.4 Hz bands	
4	96.4	96.4	96.5	[54]	ECG	HRV	RMMSD, HF, entropy, complexity, pulse waveform (HR)	HMM
5	93.8	91.3	97.3	[43]	ECG	HRV	2nd cummulant of the band 0.04–0.15 Hz or the 3rd cummulant of the band 0.15–0.5 Hz	kNN
6	92.6	–	–	[21]	Speech	Pitch	μ, min, max, median, SD, range, 1st deriv. ...	SVM
						MFCC	μ, σ^2, min and max of the 1st 12 cepstral, delta and delta-delta coefficients	
7	90.1	90.1	90.1	[65]	PD	μ		SVM
					EDA	μ		
						Orienting responses	No. of peaks, magnitude, tRise, energy	
					BVP	IBI	L/H, μ, SD	
						Amplitude		
					ST	μ		
8	90.0	95[b]	86.0	[44]	ECG	HRV	SD1, SD2, ApEn (threshold = 0.2*SDNN)	LDA
9	89	–	89[a]	[51]	EDA	μ, SD and others		SVM
					BP	μ, SD, no. of peaks and others		
					ECG	HRV	μ, SDSD and others	
					Eye gaze	Eye position	μ, SD, distance, no. of fwd. and bw. tracking fixations, eye fixation time (%) and others	
					PD	μ, SD and others		
10	88.71	–	–	[86]	PD	mean, max, Walsh coeffs.		Naïve Bayes

[a] F-score.
[b] Specificity.

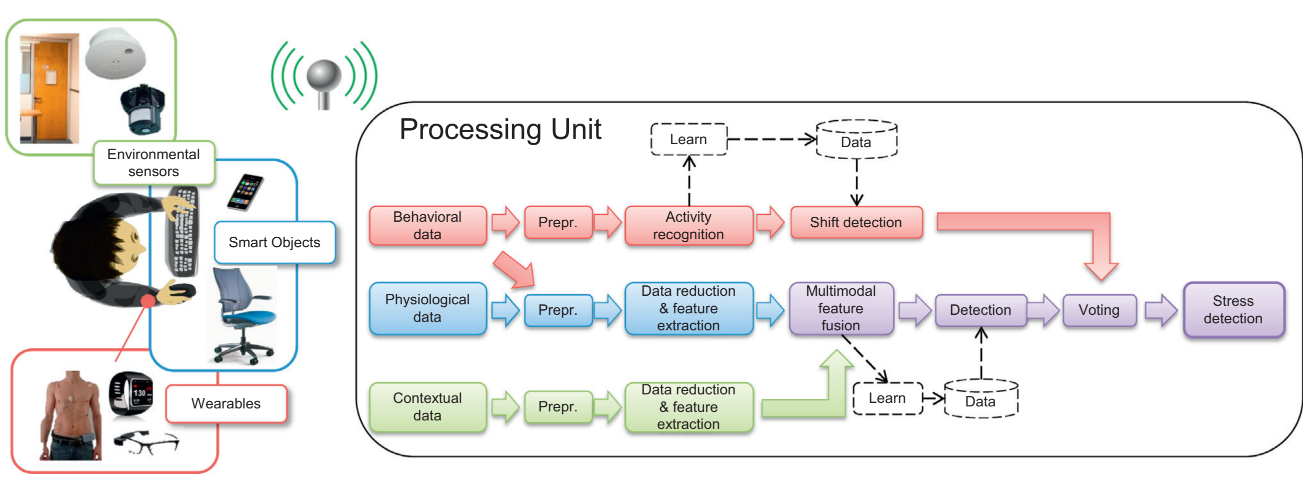

Fig. 3. A framework approach for the automatic stress recognition system.

Daily Living) monitoring a sampling frequency of 20 Hz is sufficient, while audio, speech and biomedical signals must be sampled with a higher frequency of up to 40 kHz.

Signals are easily corrupted by instrumentation noise, random noise, electric and magnetic noise, etc., as well as by poor electrode–skin contact and body movements [140], resulting in noisy and artefact containing data. Signal processing techniques are needed to remove all these undesired effects from the signals. Noise can be filtered by means of several filters, like Kalman filters, Butterworth low-pass filters, Median filers, Wiener filters, Wavelet Decomposition, etc. The selection of the best filter in each case depends on the nature of the signal, the features to be extracted, and on the type of noise [140]. Power line interference can be removed by means of a notch filter. For artefact removal, algorithms like least mean squares algorithm, regression analysis, independent component (ICA) and principal component analysis (PCA) can be used, or pressure sensors can be used in order to detect movement artefacts [141] and reject the corresponding recordings.

5.2. Integration of multimodal data

The data collected in a stress monitoring system based on multimodal measurements, will come from a wide variety of sensors and devices, and *integrating* all this data still poses some challenges.

Different acquisition systems, rely on different physical phenomena and, thereby, the resulting data is represented in different physical units. Furthermore, they do not offer the same time and space resolutions, and what's more, datasets do not have the same dimensions: whereas arrays are used for unidimensional signals' representation, matrix or tensors can be used for representing images. Even so, these difficulties can be overcome working with features extracted from the data instead of working with the raw data by itself.

Another issue to take into account is that when working with data coming from several sources, it is easy to lack data on some of them. This makes impossible to compare multimodal data at the same time points. However, possibilistic data fusion frameworks could allow to overcome this issue [142–144]. Another problem that may arise is that the data from different sources can be inconsistent. This might be solved with a voting system [145], but other solutions have also been proposed [146–148].

At what point to integrate the multimodal data in the detection system is another issue. Data can be processed separately, and merged in the final decision step; they can be sequentially processed and merged, adding new data to constrain the prior solution or they might be fused from the very beginning using a few variables from each modality, multivariate features (see Section 5.3) or minimally reduced raw data. This decision depends on the nature of data to be fused.

Finally, it must be taken into account that when merging data from different modalities, synchrony between them must be ensured.

For more details about the current challenges in data fusion the reader is referred to [130,149].

5.3. "Big data" issues

One of the biggest problems of such a system will probably be the huge amount of data being collected non-stop. This problem might be avoided with on-board signal processing algorithms, and thus, avoiding the transmission and storage of big amounts of data. Nevertheless, this affects power consumption and battery lifespan of the individual devices, as well as their storage requirements, and complexity of algorithms, so it will be a choice to make according to the equipment that is available. When this is not possible, *dimensionality reduction* of the data must be carried out, extracting the pertinent features from it, so as to ease the wireless transmission. The aim of extracting features from raw signal data is twofold: on one hand, it allows to manage much less quantity of data, while keeping all the relevant information for stress assessment, and on the other hand, it permits the data to be somehow interpreted because raw data, per se, is meaningless. Here come into place, feature extraction algorithms, being the most popular one the Principal Component Analysis (PCA) [150]. For successfully applying these algorithms in behavioural data, data segmentation may also be a critical issue: an incorrect selection of the segmentation window can lead to incorrectly infer ADLs, and the use of sliding window techniques has been recommended for the correct classification of human activity [140]. Nevertheless, in order to avoid a set of features that contains redundant information which only makes the classifier spend more time and decrease the classification accuracy, feature selection algorithms should be applied. Feature selection is a search problem which finds an optimal subset of n features out of the extracted set of N features that best discriminate between classes. This reduction in dimensionality also provides improvements in classification accuracy. Some examples of the algorithms that can be found in the literature are Sequential Forward Search (SFS) [66,151], Sequential Backward Search (SBS) [67], Correlation based feature extraction (CBFS) [94] and Genetic Algorithms (GA) [14]. For an empirical study on feature selection methods the reader is referred to [152].

Other strategies for data collection could also be considered and tested before applying the aforementioned techniques because, a completely different approach to the methodology would allow to collect much less data. Thereby, it might be preferable to continuously monitor only some part of the data (as, for example, behavioural changes), and trigger the rest of the signal monitoring (physiological signals) when suspicious changes are detected, in order to verify or reject the suspect. The validity of such a system is still to verify, mainly because it might delay the stress detection.

5.4. Unobtrusiveness, non-invasiveness and ubiquity

The unobtrusiveness and non-invasiveness of biomedical measuring devices are key factors on acceptance and satisfaction from the subjects [153].

Nowadays, technology for making this monitoring system ubiquitous and completely transparent to the user, exists. Smart offices allow to record behavioural data without disturbing the user by means of sensors integrated both in the ambient and in objects (Smart Objects), for example, in ceilings [118], chairs [101,117,141], or doors [117], and with simple monitoring software installed in computers allowing to sense the interaction activity with the computer, i.e. computer exposure [11], keyboard and mouse dynamics [37], etc. Physiological monitoring has been much more obtrusive and, thereby, a bigger issue for this kind of application. Nonetheless, nowadays, wearable devices and physiological sensors integrated into devices and textiles (E-textiles) of everyday use are making increasingly easier the measurement of physiological variables in a completely transparent way for the user. Among the examples, it is possible to find a computer mouse with photo-plethysmographic surfaces that allows to measure RR intervals enough accurately for computing HRV parameters [82], a belt for sensing breath [154], a shirt for EMG sensing [78] or a wearable ECG recorder with acceleration sensors [27].

Smart wearable systems are being increasingly used. In fact, they have already been considered for monitoring the progress of diseases such as cardiovascular [155], renal [156] or respiratory diseases [157], diabetes [158], and even cancer [159]. They can be used for monitoring patients 24 h a day, recording physiological or behavioural data, with sensors integrated in jewellery, wristwatches [160], armbands [161], shoes [162], embedded in clothes [163] and implanted in vivo [164,165]. Unfortunately, not all the physiological data can yet be unobtrusively acquired with wearable devices [166], namely, EEG requires electrodes or an electrode cap to be worn. We refer the reader to the recent review of Chan et al. [167] for a more detailed information about current wearable technology's state.

As it has been mentioned in the Section 3.3.5, smartphones also allow to acquire big amounts of data without the user being aware of it. Furthermore, apart from monitoring the characteristic behavioural features of a smartphone (e.g. number of sent SMS), these devices can be used to unobtrusively monitor other physiological or behavioural features 24 h a day. Thus, smartphones can be used to measure, for example, speech features [168] or travelled distance [66]. However, current solutions based on smartphones suffer from scalability, security and privacy issues, apart from providing only a snapshot of physiological conditions instead of a continuous and longitudinal view of the users' health status [169].

5.5. Automaticity

The system to be able to automatically detect stress, a prior learning process could be considered. The system should learn the values corresponding to the relaxed and stressed states for each individual, so that in the future, it will be able to detect stress by detecting abnormal values of these features.

For this purpose, features must be extracted and selected from the raw data. Many different algorithms have been used in precedent works for feature extraction and selection, as, for example, SFS [66,151], SBS [67], PCA [150]. Furthermore, supervised classification algorithms can be used in order to make a decision with the selected features as input. A wide variety of classifiers used for stress detection can be found in the literature, among the most interesting ones, SVM [41,51,61,70,170], LDA [41,67,111] and Fuzzy Classification [45]. For further information on how can these algorithms be applied in this application and for a comparison between them, we encourage the reader to consult some interesting reviews on these topics (see [171–173] for feature selection, [174] for classification and [175,176] for a wider overview of Data Mining).

Smart environments pose some challenges when developing completely automatic monitoring systems: when working with environment sensors that are located in distributed positions, it is necessary to interpret their information in order to infer what action is being carried out by the user. For this purpose, activity recognition algorithms are being developed and improved. Algorithms such as Hidden Markov Models or dynamic Bayesian Networks [177] have been used to model typical complex activities. Nonetheless, the correct segmentation of the sensor data streams remains still as a challenge, as well as coping with multiple users in the same environment or with multiple activities being carried out in parallel. Automatic diagnosis also requires anomalous behaviour detection, and for this purpose, the system must also be able to learn continuously and discover new non-anomalous behavioural patterns. Algorithms with these abilities have already been developed [113,115,178,179].

5.6. Interoperability

The system being proposed herein, apart from detecting stress, could be useful for a continuous health monitoring, and data being collected and treated can be practical for many other purposes. These secondary objectives might imply exchanging data between other medical devices, or with experts of the health area. Consequently, it may be interesting to develop the monitoring system following the existing standards for physiological and medical data coding and storage.

Many standards have been defined in order to overcome interoperability problems and improve the communication and data exchange between different devices all around the world. For example, the European Data Format (EDF), which has already an extended version (EDF+), was originally created for EEG and PSG recordings, but the new version also allows to store information of ECG, EMG, and Evoked Potential data, as well as annotations [180,181]. The General Data Format (GDF) for Biomedical Signals [182] derived from EDF, aiming at satisfying the needs of all the biomedical research community. An ISO standard has also been defined to assign medical waveforms' description rules in order to ensure interoperability between devices. This standard is known as Medical waveform Format Encoding Rules (MFER). As it is a general specification, it is compatible with other standards. The Standard Communication Protocol for Computer Assisted ECG (SCP-ECG) is also defined by the ISO [183], and specifies the conventions to interchange ECG signal data, measurements and interpretation results. Nowadays, the most known standards are the Digital Imaging and Communications in Medicine (DICOM) standard [184], which was created for the communication and management of medical imaging information and related data, and the standard of annotated ECGs (aECG) of the international organization Health Level 7 (HL7) [185], which is an XML-based format for the exchange of data in hospitals.

Data to be appropriately represented and to avoid them to be lost or messed, it is advisable the use of common terminology, and for this purpose, standards like the Systematized Nomenclature of Medicine – Clinical Terms (SNOMED-CT) [186] of the International Health Terminology Standards Development Organisation (IHTSDO) and the LOINC [187] which stands for "Laboratory Observations, Identifiers, Names and Codes" have been created.

5.7. Framework approach

Taking all of these issues into account, the framework represented in Fig. 3 is proposed. As it can be seen, after selecting the most appropriate signals and features to be monitored, it will be necessary to select how these data will be collected in order to ensure quality, unobtrusivity and ubiquity.

Environmental sensors placed in strategic places of the offices, common office workers' instruments in form of smart objects or comfortable wearable devices can monitor workers' physiology and behaviour, as well as the ambient variables of the offices, such as luminosity or temperature. For data transmission, collection and processing no extra equipment would be needed as the vast majority of nowadays' offices have all of them available. Namely, personal computers could be used as central processing units for all of the collected data, whereas wireless data transmission could be carried out by means of VPNs established over the widely accessible WiFi networks. Physiological and contextual data, as well as behavioural data coming from smart objects, can be treated by means of data reduction and feature extraction techniques, and fused at the feature level. Behavioural data coming from environmental sensors may require other processing in order to infer the realised activities, and how they follow or differ from the user's usual behaviour patterns. For the final fusing of data of such different modalities, another fusion system, as, for example, a voting system, could be used. As a reliable stress detection system must be modelled for individual use, due to the differences that people can reveal in their stress patterns, the intermediate decision that the system will take should be based on personal knowledge that at first can be extracted from experiments using psychological stress elicitation techniques Section 4 and later, by learning dynamically both behavioural and physiological patterns.

6. Open challenges

Nowadays, whereas technological advances allow to overcome most of the problems that could exist for the purpose herein, there are still some open challenges common for all monitoring and Telecare systems that must be addressed as soon as possible. These challenges include the following:

- Privacy, security and ethical issues:
  As stated before, such a system implies people to be continuously monitored. Therefore, huge amounts of information about

the individuals and their lives can be inferred, and unfortunately, this information may be the target of many people interested in things that have little to do with the health of individuals [188]. In fact, a Financial Times investigation revealed that 9 of the top 20 health-related mobile apps have been used to transmit data to a company interested on people's mobile phone usage [189]. Currently, approaches are being developed in order to avoid this information to be used for evil or non-ethical purposes [169,190,191]. This type of solutions must contain safety precautions such as the encryption of data and patient authentication mechanisms. The awareness of the subjects being monitored must also be assured [188], and their autonomy must be respected [192]. The current Personal Data Protection Directive of the European Union is being revised in order to give a better response to these issues posed by the development and globalisation of the new technologies [193].

- Efficiency and reliability:
  Efficiency and reliability are key characteristics for the widespread use of the developed technology [167]. It has recently been affirmed that many algorithms, for example, those used in smart environments for activity recognition, need improvements in order to become more reliable and more accurate for real life [194]. Other reports have also remarked that some solutions do not work as expected or they have not been properly tested, which in some cases may pose a risk to people's safety [195]. The European Commission adverts that errors may arise from many different sources due to the large list of stakeholders involved in the development and use of these medical devices, such as the doctor who may make an incorrect diagnosis due to inaccurate data, the IT engineer who might have introduced a bug in the code or the patient who might have misused the device [193]. This becomes a real problem if because of any of these reasons the patient is harmed, and in order to limit these risks the legal responsibilities of each stakeholder should be clearly stated. Furthermore, safety must be demonstrated by safety standards such as the IEC 82304-1 [196] or specific quality labels, and certifications might be used for ensuring the credibility of the health solutions [193].
- Cost:
  Costs associated with such a system include the first investments, as well as maintenance and operational costs. Even if the research stage of the stress detection system might be funded, the lack of financing structure for the continuation of the project can make all the work come to nothing as it has already happened with some telemedicine applications [197–200]. It has been affirmed that the high cost of current wearable system services limits their expansion and that this economic issues have to be addressed to ensure the opening of the market to these new technological systems [167]. The European Commission also accepts that the lack of innovative and adequate refund models for electronic health solutions is a major obstacle in their development and in their spread. Even if some insurance companies are adopting measures, most of them do not yet have standard tariffs for these applications [193,201,202].
- Interoperability:
  As it has been mentioned in the previous section, some standards for medical data collection and storage have been developed. Nonetheless, standards are not yet available for all the necessary aspects of telemedicine [200,203].The European Commission affirms that interoperability problems are one of the most important issues that avoid investments in these devices to be well-used and therefore, limit the scalability of this kind of solutions. Interoperability is not guaranteed without globally accepted standards, and hence, the existing standards must be adopted by systems all over the world. This might be complicated due to the wide heterogeneity of health information systems, and because millions of terminologies and vocabulary are required to describe and codify health data [193], but as it is a priority for the successful development of emerging health services, the first steps towards interoperability of electronic health systems in the EU have already been taken [204].
- Legislation:
  Legislation and policy for certain aspects of telemedicine are not yet available [194,200], albeit they are a prerequisite for the development of the system described herein. Licensure, certification and protection must be standardised in terms of laws inside the European Communities, specially, if services are to be given over the internet [167].

7. Conclusions

Stress is a growing problem in our society, and nowadays job issues, including high workloads and need of adaptation to constant changes, only serve to worsen the problem. People are suffering from health problems derived from too high stress levels, while major losses of money are elicited in enterprises. Thus, it is important to monitor and control employees' stress levels continuously in order to detect stress in its early stages and prevent the harmful long-term consequences.

Stress measuring methods based on hormonal techniques and on subjective questionnaires are not suitable for real time monitoring and require people to get out of their routine activities.

Changes in some physiological features have been associated with changes in stress levels, but there are many conflicts to be solved yet. Physiological changes due to stress are not always reflected the same way in all individuals, making more difficult the development of a detection system based on this kind of information. A system that is able to adapt itself to each individual's physiology should be considered. Furthermore, the discomfort provoked by most of the physiological monitoring devices is still to overcome if they are going to be used in real-life activities. Apart from the classical psychological stress assessing methods, behavioural monitoring systems, as well as contextual information, are being more and more considered in the stress detection field. Methods which do not require expensive hardware and are not highly intrusive are being analysed and opening the doors to new opportunities. Nevertheless, there is much work to do to gain enough reliability in this kind of systems.

An analysis of the measurement systems and features of different modalities used in the literature has been done in this research. A summary of the reviewed literature can be found in Table 5. The most accurate stress detection systems developed in the state of the art show that stress detection using physiological signals is much more accomplished than using the rest of the modalities. This does not mean that behavioural and contextual information do not have the potential to correctly detect stress, as results of the literature prove they do, but that there is still much work to do in this area. The results also suggest that ECG, especially using HRV features, and EDA are the most accurate physiological signals for recognising stress. The same or bigger accuracies would be desired using other modalities' information, such as the behavioural responses, to develop a much less intrusive and ubiquitous monitoring system, which would be much more practical for the real life.

It is evident that stress, being a problem that affects in many aspects of a human being, a real-life stress monitoring system cannot be developed considering only one of the modalities, i.e. it cannot be reliable enough if it is based only on physiological signals or behavioural responses. Thereby, a multimodal technique must be considered.

There have been some difficulties for fusing data of different modalities until now, but nowadays most of them are solved.

Table 5
Summary of reviewed literature.

Reference	Target	Classes	Subj.	Ground truth	Elicitation	Signals	F. selec.	Decision	Accuracy
Cinaz et al. [41]	Workload	3	7 (m)	Nasa TLX and salivary cortisol	Arithmetics	ECG	Corr. based	MR analysis, LDA, kNN, SVM	7/8 subjects
Wijsman et al. [15]	Stress	2	30	PSS and VAS	Calculation, memory, logical tasks	ECG, EDA, Resp, EMG	Corr. based	Generalized Estimating Equations	80%, 69.1% (S/NS) (avg 74.5%)
Palanisamy et al. [43]	Stress	2	40	An effectiveness report	Arithmetics	ECG, EMG, EDA, ST	–	kNN, PNN	HRV: 93.75%, ECG: 76.25%, EDA: 70.83%, ST: 75.32%, EMG: 71.25%
Melillo et al. [44]	Stress	2	42	–	Exam/Holidays	ECG	Exhaustive Search Method	LDA	90%
Seo et al. [32]	Stress	2	33	SRI, SAM, Salivary cortisol	Visual stimuli (un) pleasant imag.	EEG, ECG, cortisol	–	No decision: corr. analysis	–
Rahnuma et al. [57]	Emotion	4	4	–	IAPS emotion stimuli	EEG	–	MLP	96.4%
Zhang et al. [59]	Workload	2	16	STAI	Cognitive tasks: visual reaction, stroop, fast counting, memory,...	EEG, EDA, HRV	–	LMUR	EEG: 87.5%, EDA: 75%, HRV: 62.5%
Healey et al. [50]	Stress	3	–	Questionnaire and a score derived from videos	Driving task	EDA, ECG, EMG, Resp	–	LDA	100%, 94.7% and 97.4% for low, medium and high stress levels
De Santos Sierra et al. [45]	Stress	2	80 (f)	–	Hyperventilation and Talk Preparation	EDA, ECG	–	Fuzzy Logic, GMM, kNN, Discriminant Anal., SVM	Fuzzy Logic: 99.5% (Recall)
Seoane et al. [64]	Stress	4	42	SAM, Profile of Mood States	Videos, games, exercise	EDA, ST, ECG, Resp, voice	GA	LDC	ECG: 76.28%
Sharma and Gedeon [51]	Stress	2	35	Survey	Reading S/NS texts	EDA, ECG, BP, eye gaze, PD	GA	ANN and SVM	GA-SVM: 89%
Kocielnik et al. [38],	Stress	–	10	–	–	ST, EDA, accelerometer, ambient illumination, calendar events	–	–	–
Zhai et al. [65],	Stress	2	32	–	Stroop	PD, BVP, EDA and ST	–	Naïve Bayes, DT, SVM	SVM: 90.1%
Maaoui et al.	Emotion	6	10	SAM	IAPS	BVP, EMG, EDA, ST, Resp	–	Fisher Discriminant and SVM	SVM: 90% ind. models, 45% general model
Wijsman et al. [76]	Stress	2	22	PSS and self-report questionnaire	Calculation, logical and memory tasks	EMG	–	No decision: corr. analysis	–
Wei [77]	Stress	2	1	–	Tetris game	EMG and Resp	–	Fisher Discriminant	EMG: 97.8%, Resp: 86.7%
Shi et al. [79]	Stress	2	22	EMA	Public speaking, cold, arithmetic	ECG, EDA, Resp, ST	–	SVM (linear and RBF)	56% ind. models, 62% general models (precision)
Liao et al. [26]	Stress	–	5	–	Math task, audio task	Blink f., eye gaze, PD, head movement, facial expression, ECG, ST, EDA, mouse dynamics, error rates, response times	–	No decision: corr. analysis	–
Sakamoto et al. [85]	Emotion	–	6	Interviews	Categorizing cognitive task	PD, ECG	–	No decision: corr. analysis	–
Ren et al. [86]	Stress	2	31	Self-Assesment test	Stroop	EDA and PD	–	K∗, MLP, Naïve Bayes, RF, Jrip	Naïve Bayes and PD: 88.71%
Haak et al. [88]	Stress	–	1	–	Car-driving simulation	Eye blinks from EEG	–	No decision: corr. analysis	–
Norzali et al. [72]	Stress	–	5	–	Color word test	Facial ST by TI, Blood Volume, BF	–	No decision, corr. analysis	–
Levine et al. [75]	Stress	–	–	–	Stroop, arithmetic	TI	–	No decision: corr. analysis	–

Sharma et al. [14]	Stress	2	35	Survey	Watch S/NS videos	TI, visual facial patterns	GA	SVM	86%
Chen et al. [90]	Stress	2	21	Salivary cortisol, HR	TSST	Hyperspectral Imaging	–	Binary classifier	Auto. threshold: 76.19%, Manual threshold: 88.1%
Hayashi et al. [29]	Stress	2	33	SSRS, VAS, CMI	Emotional audio-visual stimuli	fMRI	–	No decision, corr. analysis	–
Hernandez et al. [37]	Stress	–	24	Survey of valence, arousal and stress levels, EDA, accelerometer, ST	Text transcription, expressive writing, mouse clicking	Keyboard and mouse dynamics	–	No decision, significance levels	–
Salmeron-Majadas et al. [98]	Emotion (Valence)	2	17	SAM, description of feelings	IAPS, arithmetic and logical tasks	Keyboard and mouse dynamics	–	C4.5, Naïve Bayes, Bagging, RF, AdaBoost	RF and AdaBoost: 59%
Anrich et al. [101]	Stress	2	28 (m)	–	MIST stress and cognitive load tasks	Physiological signals, acceleration, sitting pressure	–	SOM	73.75%
McDuff et al. [30]	Emotion	2	5	Self-reported valence, arousal and engagement levels	–	Posture, facial expressions, EDA, speech, head movements, calendar events, GPS, file activity	–	kNN	68%
Dinges et al. [103]	Stress	2	60	Self-reports, salivary cortisol measures and HR signals	Workload and social feedback	Facial expressions	–	HMM	75–88%
Das and Yamada [106]	Stress	–	105 expressions	A survey	Posed expressions	Facial expressions	–	Regression analysis + math. formula	–
Lu et al. [108],	Stress	2	14	EDA	Job interview and marketing job	Voice from mobile phones, accelerometer, GPS	–	GMM	General: 71.3% in. 66.6% out. Individual: 82.9% in. 77.9% out.
Demenko et al. [111]	Stress	2	45	Manually labelled arousal levels	Emergency phone call DB	Voice from calls	–	LDA	84%
Kurniawan et al. [21]	Stress	2	230 instances	–	Stroop, TSST, TMCT	Speech, facial expressions and EDA	–	K-means, GMM, SVM	EDA: 80.72%, Speech: 92.6%, Both: 92.4% (SVM)
Muaremi et al. [112]	Stress	3	35	PANAS	–	Audio, acceleration, GPS, mobile phone usage, calendar, ECG	Cross-corr. + SFS	Multinomial Logistic Regression	Phone: 55%, HRV: 59%, Both: 61%
Sano et al. [66]	Stress	2	18	PSS, PSQI, BFIPT	–	EDA, accelerometer, mobile phone usage	SFFS, PCA	Linear and RBF SVM, kNN	75%
Eijckelhof et al. [11]	Stress	–	93	PSS, ERI, "the need for control model"	–	Computer usage patterns	Corr. based	Linear Regression (corr. analysis)	–
Suryadevara et al. [119]	Emotion	–	–	–	–	HR, ST, EDA, smart home behaviour patterns	–	–	–
Saleem et al. [128]	Stress	–	512 threads (5000 messages)	Manually labeled	–	Sentiment analysis from forum texts		SVM, MLN (Markov Logic Networks)	MLN: 0.4515 AUC
Vizer et al. [36]	Stress	3	24	Survey Likert Scale	Arithmetics and memory and physical stress	Keyboard dynamics and linguistic features	DT	DT, SVM, kNN, AdaBoost, ANN	62.5% (physical), 75% (cognitive)
Peternel et al. [16]	Stress	7	–	–	–	Location, activity, mobile phone use, computer use, ambient audio	–	HMM	–
Sharma and Gedeon [60]	Stress	2	(25 + 40) 65	Survey Likert Scale	Interview & mediation settings	EEG, EDA, TI	GA	SVM	98%
Li et al. [54]	Stress	5	39	A questionnaire	Workload, strange phone calls, audio–videos, threatening letters, exam notification	ECG	–	HMM	96.4%

Feature-level fusion and voting systems could be used for merging data of different nature, allowing at the same time to reduce the amount of information to work with. Furthermore, continuous and unobtrusive monitoring can be assured thanks to devices of low consumption in the form of wearables, smart devices and ambient sensors, which send data via wireless connections to the processing units. Offices are the perfect environment for such a system, because they already have the necessary infrastructure such as personal computers, which can be used for data processing, and WiFi connections for creating the wireless sensor networks. AI algorithms that allow the automatic pattern learning and detection of anomalies are also available. One of the few issues that might need improvements is the fact of dealing with multiple-users in the same environment, which can be of great importance in offices.

Moreover, there are still some few open challenges concerning all ubiquitous health systems which are delaying the adoption of mobile health and telehealth systems in our society. These challenges include privacy, security and ethical issues, as well as financial affairs and the lack of reliability of some existing health applications that must be overcome for these devices and systems to be affordable for everyone. Interoperability standards should also start being used by all of these systems, and the necessary legislation must be defined in order to avoid both physical and privacy-related security problems. Steps are already being taken in order to overpass all these issues and promote the development and widespread use of ubiquitous health systems which can arrive in the very near future.

Therefore, future work must be carried out combining information of different modalities and creating methods for obtaining this information in a totally unobtrusive, but ubiquitous way, which is necessary for a practical real-life monitoring. A framework that aims at integrating all the existing technology that could aid in creating such a system has been proposed in this paper, as well as reviewing the open challenges that must be overcome in order to definitely be able to create and widespread use this kind of technology. Suggestions for correctly collecting and integrating the data have been done, as well as other recommendations for overcoming issues related to the great amount of data, to the ubiquity and automaticity and to the interoperability between devices.

In conclusion, with a few further research, a system which involves all the aforementioned characteristics and helps improving people's life quality avoiding or greatly reducing the current stress-related problems will be reached.

Conflict of interest

The authors have declared no conflict of interest.

Acknowledgements

The authors would like to thank the anonymous reviewers for the detailed analysis and helpful comments.

References

[1] European Agency for Safety and Health at Work, Campaign guide: managing stress and psychosocial risks at work, 2013. doi:http://dx.doi.org/10.2802/57908.

[2] T.W. Colligan, E.M. Higgins, Workplace stress, J. Workplace Behav. Health 21 (2) (2006) 89–97, http://dx.doi.org/10.1300/J490v21n02_07. <http://www.tandfonline.com/doi/abs/10.1300/J490v21n02_07>.

[3] B. Cosemans, Marlen Cosmar, Robert Gründler, Danny Flemming, K. Van, Calculating the cost of work-related stress and psychosocial risks, Tech. rep., European Agency for Safety and Health at Work, Luxembourg, 2014. doi:http://dx.doi.org/10.2802/20493.

[4] M. Milczarek, Elke Schneider, E.R. González, OSH in figures, stress at work, facts and figures, Tech. rep., European Agency for Safety and Health at Work, Luxembourg, 2009. <https://osha.europa.eu/en/publications/reports/TE-81-08-478-EN-C_OSH_in_figures_stress_at_work>.

[5] European Agency for Safety and Health at Work, European Opinion Poll on Occupational Safety and Health, Tech. rep. May, European Agency for Safety and Health at Work, Bilbao, Spain, 2013. doi:http://dx.doi.org/10.2802/55505. <https://osha.europa.eu/en/safety-health-in-figures/eu-poll-press-kit-2013.pdf>.

[6] H. Selye, The Stress of Life, McGraw-Hil Edition, New York, 1956.

[7] R.S. Lazarus, S. Folkman, Stress, Appraisal, and Coping, Springer Publishing Company, New York, USA, 1984.

[8] B.S. McEwen, The neurobiology of stress: from serendipity to clinical relevance, Brain Res. 886 (1–2) (2000) 172–189, http://dx.doi.org/10.1016/S0006-8993(00)02950-4. <http://linkinghub.elsevier.com/retrieve/pii/S0006899300029504>.

[9] B. Mishra, S. Mehta, N.D. Sinha, S.K. Shukla, N. Ahmed, A. Kawatra, Evaluation of work place stress in health university workers: a study from rural India, Indian J. Commun. Med.: Official Publ. Indian Assoc. Preventive Soc. Med. 36 (1) (2011) 39–44, http://dx.doi.org/10.4103/0970-0218.80792. <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3104707&tool=pmcentrez&rendertype=abstract>.

[10] Andrea Broughton (Institute for Employment Studies (IES)), Work-related stress, Tech. rep., European Foundation for the Improvement of Living and Working Conditions, Dublin, 2010. <http://eurofound.europa.eu/observatories/eurwork/comparative-information/work-related-stress>.

[11] B.H.W. Eijckelhof, M.A. Huysmans, B.M. Blatter, P.C. Leider, P.W. Johnson, J.H. van Dieën, J.T. Dennerlein, A.J. van der Beek, Office workers' computer use patterns are associated with workplace stressors, Appl. Ergonomics 45 (6) (2014) 1660–1667, http://dx.doi.org/10.1016/j.apergo.2014.05.013. <http://www.ncbi.nlm.nih.gov/pubmed/25005311>.

[12] Health and Safety Authority, Workplace Health Toolkit for Small Businesses, Tech. rep., Health and Safety Authority, 2010.

[13] J. Bakker, M. Pechenizkiy, N. Sidorova, What's your current stress level? Detection of stress patterns from GSR sensor data, in: Proceedings – IEEE International Conference on Data Mining, ICDM, IEEE, 2011, pp. 573–580. vol. 1, doi:http://dx.doi.org/10.1109/ICDMW.2011.178. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6137431>.

[14] N. Sharma, A. Dhall, T. Gedeon, R. Goecke, Thermal spatio-temporal data for stress recognition, EURASIP J. Image Video Process. 2014 (1) (2014) 28, http://dx.doi.org/10.1186/1687-5281-2014-28. <http://jivp.eurasipjournals.com/content/2014/1/28>.

[15] J. Wijsman, B. Grundlehner, H. Liu, J. Penders, H. Hermens, Wearable physiological sensors reflect mental stress state in office-like situations, in: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, IEEE, 2013, pp. 600–605. vol. iii, doi:http://dx.doi.org/10.1109/ACII.2013.105. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6681496>.

[16] K. Peternel, M. Pogačnik, R. Tavčar, A. Kos, A presence-based context-aware chronic stress recognition system, Sensors (Basel, Switzerland) 12 (11) (2012) 15888–15906, http://dx.doi.org/10.3390/s121115888. <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3522991&tool=pmcentrez&rendertype=abstract>.

[17] M. Bickford, Stress in the workplace: a general overview of the cases, the effects and the solutions, Tech. rep. August, Canadian Mental Health Association, 2005. <http://www.cmhanl.ca/pdf/WorkPlaceStress.pdf>.

[18] N. Sharma, T. Gedeon, Objective measures, sensors and computational techniques for stress recognition and classification: a survey, Comput. Methods Programs Biomed. 108 (3) (2012) 1287–1301, http://dx.doi.org/10.1016/j.cmpb.2012.07.003. <http://www.ncbi.nlm.nih.gov/pubmed/22921417>.

[19] Engineering Village, <http://www.engineeringvillage.com/>.

[20] US National Library of Medicine National Institutes of Health, PubMed central, <http://www.ncbi.nlm.nih.gov/pmc/>.

[21] H. Kurniawan, A.V. Maslov, M. Pechenizkiy, Stress detection from speech and galvanic skin response signals, in: Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems, 2013, pp. 209–214. doi:http://dx.doi.org/10.1109/CBMS.2013.6627790. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6627790>.

[22] A. Kaklauskas, E.K. Zavadskas, M. Seniut, G. Dzemyda, V. Stankevic, C. Simkevičius, T. Stankevic, R. Paliskiene, A. Matuliauskaite, S. Kildiene, L. Bartkiene, S. Ivanikovas, V. Gribniak, Web-based biometric computer mouse advisory system to analyze a user's emotions and work productivity, Eng. Appl. Artif. Intell. 24 (6) (2011) 928–945, http://dx.doi.org/10.1016/j.engappai.2011.04.006. <http://linkinghub.elsevier.com/retrieve/pii/S0952197611000662>.

[23] Psychological, 2015. <http://www.collinsdictionary.com/dictionary/english/psychological?showCookiePolicy=true>.

[24] Physiology, 2015. <http://www.oxforddictionaries.com/definition/english/physiology>.

[25] Behavior, 2015. <http://www.merriam-webster.com/dictionary/behavior>.

[26] W. Liao, W. Zhang, Z. Zhu, Q. Ji, A real-time human stress monitoring system using dynamic bayesian network, in: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) – Workshops 3, 2005, pp. 70–70. doi:http://dx.doi.org/10.1109/CVPR.2005.394. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1565377>.

[27] Y. Okada, T.Y. Yoto, T.-a. Suzuki, S. Sakuragawa, T. Sugiura, Wearable ECG recorder with acceleration sensors for monitoring daily stress: office work simulation study, in: Conference Proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE

Engineering in Medicine and Biology Society, Annual Conference, 2013, pp. 4718–4721. doi:http://dx.doi.org/10.1109/EMBC.2013.6610601. <http://www.ncbi.nlm.nih.gov/pubmed/24110788>.

[28] D. Carneiro, J.C. Castillo, P. Novais, A. Fernández-Caballero, J. Neves, Multimodal behavioral analysis for non-invasive stress detection, Expert Syst. Appl. 39 (18) (2012) 13376–13389, http://dx.doi.org/10.1016/j.eswa.2012.05.065. <http://linkinghub.elsevier.com/retrieve/pii/S0957417412007816>.

[29] T. Hayashi, Y. Mizuno-Matsumoto, E. Okamoto, M. Kato, T. Murata, An fMRI study of brain processing related to stress states, in: World Automation Congress (WAC), 2012, IEEE, Puerto Vallarta, Mexico, 2012, pp. 1–6. <http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6320900&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D6320900>.

[30] D. McDuff, A. Karlson, A. Kapoor, A. Roseway, M. Czerwinski, AffectAura: an intelligent system for emotional memory, in: Proceedings of the 2012 ACM Annual Conference on Human Factors in Computing Systems – CHI '12, ACM Press, New York, New York, USA, 2012, p. 849. doi:http://dx.doi.org/10.1145/2207676.2208525. <http://dl.acm.org/citation.cfm?doid=2207676.2208525>.

[31] P. Zimmermann, S. Guttormsen, B. Danuser, P. Gomez, Affective computing – a rationale for measuring mood with mouse and keyboard, Int. J. Occupational Safety Ergonomics: JOSE 9 (2003) 539–551. doi:9507598 [pii].

[32] S.-h. Seo, J.-t. Lee, Stress and EEG, in: M. Crisan (Ed.), Convergence and Hybrid Information Technologies, March, 2010, p. 426. doi:http://dx.doi.org/10.5772/235. <http://www.intechopen.com/books/convergence-and-hybrid-information-technologies>.

[33] K. Darton, How to manage stress, Mind 2012, London, 2014. <http://www.mind.org.uk/media/977061/how-to-manage-stress-2012-2-.pdf>.

[34] S.J. Lupien, F. Seguin, How to Measure Stress in Humans, Tech. rep., Centre for Studies on Human Stress, Quebec, 2013. <http://www.humanstress.ca/documents/pdf/SalivaLab/HOWTOMEASURESTRESS_CSHS.pdf>.

[35] D.H. Hellhammer, S. Wüst, B.M. Kudielka, Salivary cortisol as a biomarker in stress research, Psychoneuroendocrinology 34 (2) (2009) 163–171, http://dx.doi.org/10.1016/j.psyneuen.2008.10.026. <http://www.ncbi.nlm.nih.gov/pubmed/19095358>.

[36] L.M. Vizer, L. Zhou, A. Sears, Automated stress detection using keystroke and linguistic features: an exploratory study, Int. J. Human–Comput. Stud. 67 (10) (2009) 870–886, http://dx.doi.org/10.1016/j.ijhcs.2009.07.005. <http://linkinghub.elsevier.com/retrieve/pii/S1071581909000937>.

[37] J. Hernandez, P. Paredes, A. Roseway, M. Czerwinski, Under pressure: sensing stress of computer users, in: Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems – CHI '14, ACM Press, New York, New York, USA, 2014, pp. 51–60. doi:http://dx.doi.org/10.1145/2556288.2557165. <http://dl.acm.org/citation.cfm?doid=2556288.2557165>.

[38] R. Kocielnik, N. Sidorova, F.M. Maggi, M. Ouwerkerk, J.H.D.M. Westerink, Smart technologies for long-term stress monitoring at work, in: Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems, IEEE, 2013, pp. 53–58. doi:http://dx.doi.org/10.1109/CBMS.2013.6627764. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6627764>.

[39] E.J. Berbari, Principles of electrocardiography, in: J.D. Bronzino (Ed.), The Biomedical Engineering Handbook, second ed., CRC Press LLC, Boca Raton, 2000.

[40] K. Asai, The Role of Head-Up Display in Computer-Assisted Instruction, Human Computer Interaction: New Developments, Available from: arXiv:1001.0420, doi:http://dx.doi.org/10.5772/85. <http://www.intechopen.com/books/human_computer_interaction_new_developments http://arxiv.org/abs/1001.0420>.

[41] B. Cinaz, B. Arnrich, R. La Marca, G. Tröster, Monitoring of mental workload levels during an everyday life office-work scenario, Personal Ubiquitous Comput. 17 (2) (2013) 229–239, http://dx.doi.org/10.1007/s00779-011-0466-1. <http://link.springer.com/10.1007/s00779-011-0466-1>.

[42] S. Mika, G. Ratsch, J. Weston, B. Scholkopf, K. Mullers, Fisher discriminant analysis with kernels, in: Neural Networks for Signal Processing IX: Proceedings of the 1999 IEEE Signal Processing Society Workshop (Cat. No. 98TH8468), doi:http://dx.doi.org/10.1109/NNSP.1999.788121.

[43] K. Palanisamy, M. Murugappan, S. Yaacob, Multiple physiological signal-based human stress identification using non-linear classifiers, Electron. Electr. Eng. 19 (7) (2013) 80–85, http://dx.doi.org/10.5755/j01.eee.19.7.2232. <http://www.eejournal.ktu.lt/index.php/elt/article/view/2232>.

[44] P. Melillo, M. Bracale, L. Pecchia, Nonlinear heart rate variability features for real-life stress detection. Case study: students under stress due to university examination, BioMed. Eng. OnLine 10 (1) (2011) 96, http://dx.doi.org/10.1186/1475-925X-10-96.

[45] A. de Santos Sierra, C. Sanchez Avila, G. Bailador del Pozo, J. Guerra Casanova, Stress detection by means of stress physiological template, in: 2011 Third World Congress on Nature and Biologically Inspired Computing, 2011, pp. 131–136. doi:http://dx.doi.org/10.1109/NaBIC.2011.6089448. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6089448>.

[46] J. Ramos, J.-h. Hong, A.K. Dey, Stress recognition – a step outside the lab, in: Proceedings of the International Conference on Physiological Computing Systems, SCITEPRESS – Science and Technology Publications, 2014, pp. 107–118. doi:http://dx.doi.org/10.5220/0004725701070118. <http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220/0004725701070118>.

[47] N. Karim, J.A. Hasan, S.S. Ali, Heart rate variability: a review, J. Basic Appl. Sci. 7 (1) (2011) 71–77.

[48] J. Sztajzel, Heart rate variability: a noninvasive electrocardiographic method to measure the autonomic nervous system, Swiss Med. Weekly 134 (35–36) (2004) 514–522. doi:2004/35/smw-10321, <http://www.ncbi.nlm.nih.gov/pubmed/15517504>.

[49] N. Hjortskov, D. Rissén, A.K. Blangsted, N. Fallentin, U. Lundberg, K. Søgaard, The effect of mental stress on heart rate variability and blood pressure during computer work, Eur. J. Appl. Physiol. 92 (1–2) (2004) 84–89, http://dx.doi.org/10.1007/s00421-004-1055-z. http://dx.doi.org/10.1007/s00421-004-1055-z\nhttp://www.springerlink.com/content/tawr8yuyqt0fk0kf/http://www.ncbi.nlm.nih.gov/pubmed/14991326.

[50] J.A. Healey, R.W. Picard, Detecting stress during real-world driving tasks using physiological sensors, IEEE Trans. Intell. Transport. Syst. 6 (2) (2005) 156–166, http://dx.doi.org/10.1109/TITS.2005.848368. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1438384>.

[51] N. Sharma, T. Gedeon, Hybrid genetic algorithms for stress recognition in reading, in: L. Vanneschi, W.S. Bush, M. Giacobini (Eds.), Evolutionary Computation, Machine Learning and Data Mining in Bioinformatics, Lecture Notes in Computer Science, vol. 7833, Springer, Berlin, Heidelberg, 2013, pp. 117–128. doi:http://dx.doi.org/10.1007/978-3-642-37189-9. <http://link.springer.com/10.1007/978-3-642-37189-9>.

[52] J. Choi, R. Gutierrez-Osuna, Using heart rate monitors to detect mental stress, in: 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, IEEE, Berkeley, CA, 2009, pp. 219–223. doi:http://dx.doi.org/10.1109/BSN.2009.13. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5226888>.

[53] T. Hayashi, E. Okamoto, H. Nishimura, Y. Mizuno-Matsumoto, R. Ishii, S. Ukai, Beta activities in EEG associated with emotional stress, Int. J. Intell. Comput. Med. Sci. Image Process. 3 (1) (2009) 57–68, http://dx.doi.org/10.1080/1931308X.2009.10644171. <http://www.tandfonline.com/doi/abs/10.1080/1931308X.2009.10644171>.

[54] X. Li, Z. Chen, Q. Liang, Y. Yang, Analysis of mental stress recognition and rating based on hidden Markov model, J. Comput. Informa. Syst. 10 (18) (2014) 7911–7919, http://dx.doi.org/10.12733/jcis11559. <http://www.jofcis.com>.

[55] V. Malhotra, M.K. Patil, Mental stress assessment of ECG signal using statistical analysis of bio-orthogonal wavelet coefficients, Int. J. Sci. Res. (IJSR) 2 (12) (2013) 430–434. <http://www.ijsr.net/archive/v3i2/MDUwMjE0MDE=.pdf>.

[56] W.J. Ray, H.W. Cole, EEG alpha activity reflects attentional demands, and beta activity reflects emotional and cognitive processes, Science (New York, N.Y.) 228 (4700) (1985) 750–752, http://dx.doi.org/10.1126/science.3992243. <http://www.ncbi.nlm.nih.gov/pubmed/3992243>.

[57] K.S. Rahnuma, A. Wahab, N. Kamaruddin, H. Majid, EEG analysis for understanding stress based on affective model basis function, in: 2011 IEEE 15th International Symposium on Consumer Electronics (ISCE), IEEE, 2011, pp. 592–597. doi:http://dx.doi.org/10.1109/ISCE.2011.5973899. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5973899>.

[58] J.A. Russel, A circumplex model of affect, J. Personality Soc. Psychol. 39 (6) (1980) 1161–1178.

[59] H. Zhang, Y. Zhu, J. Maniyeri, C. Guan, Detection of variations in cognitive workload using multi-modality physiological sensors and a large margin unbiased regression machine, in: Conference Proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society, Annual Conference 2014 (November 2015), 2014, pp. 2985–2988. doi:http://dx.doi.org/10.1109/EMBC.2014.6944250. <http://www.scopus.com/inward/record.url?eid=2-s2.0-84929471890&partnerID=tZOtx3y1>.

[60] N. Sharma, T. Gedeon, Modeling observer stress for typical real environments, Expert Syst. Appl. 41 (5) (2014) 2231–2238, http://dx.doi.org/10.1016/j.eswa.2013.09.021. <http://linkinghub.elsevier.com/retrieve/pii/S0957417413007550>.

[61] O. Sourina, Y. Liu, EEG-enabled affective human–computer interfaces, in: C. Stephanidis, M. Antona (Eds.), Universal Access in Human–Computer Interaction: Design and Development Methods for Universal Access, Lecture Notes in Computer Science, vol. 8513, Springer International Publishing, Cham, 2014, pp. 536–547. doi:http://dx.doi.org/10.1007/978-3-319-07437-5. <http://link.springer.com/10.1007/978-3-319-07437-5>.

[62] T. Roh, K. Bong, S. Hong, H. Cho, S. Member, H.-j. Yoo, Wearable mental-health monitoring platform with independent component analysis and nonlinear chaotic analysis, in: 34th Annual International Conference of the IEEE EMBS, San Diego, California, USA, 2012, pp. 4541–4544.

[63] J. Peuscher, Galvanic skin response (GSR), Tech. rep. November, TMSI, 2012. <http://www.tmsi.com/products/accessories?task=callelement&format=raw&item_id=43&element=fe0c95f3-af08-4719-bc51-36917715660d&method=download>.

[64] F. Seoane, I. Mohino-Herranz, J. Ferreira, L. Alvarez, R. Buendia, D. Ayllón, C. Llerena, R. Gil-Pita, Wearable biomedical measurement systems for assessment of mental stress of combatants in real time, Sensors (Basel, Switzerland) 14 (4) (2014) 7120–7141, http://dx.doi.org/10.3390/s140407120. <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4029694&tool=pmcentrez&rendertype=abstract>.

[65] J. Zhai, A. Barreto, Stress detection in computer users based on digital signal processing of noninvasive physiological variables., in: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society, Annual Conference, vol. 1, 2006,

pp. 1355–1358. doi:http://dx.doi.org/10.1109/IEMBS.2006.259421. <http://www.ncbi.nlm.nih.gov/pubmed/17946041>.
[66] A. Sano, R.W. Picard, Stress recognition using wearable sensors and mobile phones, in: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, 2013, pp. 671–676. doi:http://dx.doi.org/10.1109/ACII.2013.117. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6681508>.
[67] D. Giakoumis, D. Tzovaras, G. Hassapis, Subject-dependent biosignal features for increased accuracy in psychological stress detection, Int. J. Human–Comput. Stud. 71 (4) (2013) 425–439, http://dx.doi.org/10.1016/j.ijhcs.2012.10.016. <http://linkinghub.elsevier.com/retrieve/pii/S1071581912001760>.
[68] T. Pickering, Principles and techniques of blood pressure measurement, Cardiol. Clinics 28 (4) (2002) 571–586, http://dx.doi.org/10.1016/j.ccl.2010.07.006.Principles. <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:principles+and+techniques+of+blood+pressure+measurement#0>.
[69] M. Quazi, S.C. Mukhopadhyay, N.K. Suryadevara, Y. Huang, Towards the smart sensors based human emotion recognition, in: 2012 IEEE International Instrumentation and Measurement Technology Conference Proceedings, IEEE, 2012, pp. 2365–2370. doi:http://dx.doi.org/10.1109/I2MTC.2012.6229646. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6229646>.
[70] C. Maaoui, A. Pruski, F. Abdat, Emotion recognition for human-machine communication, in: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2008, pp. 1210–1215. doi:http://dx.doi.org/10.1109/IROS.2008.4650870. <http://www.intechopen.com/source/pdfs/12200/InTech-Emotion_recognition_through_physiological_signals_for_human_machine_communication.pdf. http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4650870>.
[71] S. Begum, M. Ahmed, P. Funk, N. Xiong, B.V. Schéele, Using calibration and fuzzification of cases for improved diagnosis and treatment of stress, Inform. Comput. (1991) 93–172.
[72] M. Norzali, H. Mohd, M. Kashima, K. Sato, M. Watanabe, Facial visual-infrared stereo vision fusion measurement as an alternative for physiological measurement, J. Biomed. Image Process. 1 (May) (2014) 34–44.
[73] C. Puri, L. Olson, I. Pavlidis, J. Levine, J. Starren, StressCam, in: CHI '05 Extended Abstracts on Human Factors in Computing Systems – CHI '05, ACM Press, New York, USA, 2005, p. 1725. doi:http://dx.doi.org/10.1145/1056808.1057007. <http://portal.acm.org/citation.cfm?doid=1056808.1057007>.
[74] K. Nakayama, S. Goto, K. Kuraoka, K. Nakamura, Decrease in nasal temperature of rhesus monkeys (*Macaca mulatta*) in negative emotional state, Physiol. Behav. 84 (5) (2005) 783–790, http://dx.doi.org/10.1016/j.physbeh.2005.03.009. <http://www.ncbi.nlm.nih.gov/pubmed/15885256>.
[75] J.A. Levine, I.T. Pavlidis, L. MacBride, Z. Zhu, P. Tsiamyrtzis, Description and clinical studies of a device for the instantaneous detection of office-place stress, Work (Reading, Mass.) 34 (3) (2009) 359–364, http://dx.doi.org/10.3233/WOR-2009-0934. <http://www.ncbi.nlm.nih.gov/pubmed/20037251>.
[76] J. Wijsman, B. Grundlehner, J. Penders, H. Hermens, Trapezius muscle EMG as predictor of mental stress, Wireless Health 2010 on – WH '10, vol. V, ACM Press, New York, USA, 2010, p. 155. doi:http://dx.doi.org/10.1145/1921081.1921100. <http://portal.acm.org/citation.cfm?doid=1921081.1921100>.
[77] C.Z. Wei, Stress emotion recognition based on RSP and EMG signals, Adv. Mater. Res. 709 (2013) 827–831, http://dx.doi.org/10.4028/www.scientific.net/AMR.709.827. <http://www.scientific.net/AMR.709.827>.
[78] J. Taelman, T. Adriaensen, C. van der Horst, T. Linz, A. Spaepen, Textile integrated contactless EMG sensing for stress analysis., in: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society, Annual Conference, vol. 2007, 2007, pp. 3966–3969. doi:http://dx.doi.org/10.1109/IEMBS.2007.4353202. <http://www.ncbi.nlm.nih.gov/pubmed/18002868>.
[79] Y. Shi, M.H. Nguyen, P. Blitz, B. French, S. Fisk, F.D. Torre, A. Smailagic, D.P. Siewiorek, M. Absi, E. Ertin, T. Kamarck, S. Kumar, Personalized stress detection from physiological measurements, in: International Symposium on Quality of Life Technology, 2010.
[80] A. Alcaine, D. Romero, E. Gil, P. Laguna, S. Leif, R. Bail, Electrocardiogram derived respiration from QRS slopes: evaluation with stress testing recordings, in: Computing in Cardiology 2013 (CinC), Piscataway, NJ, USA, 2013, pp. 655–658.
[81] E. Peper, R. Harvey, I.-m. Lin, H. Tylova, D. Moss, Is there more to blood volume pulse than heart rate variability, respiratory sinus arrhythmia, and cardiorespiratory synchrony?, Biofeedback 35 (2) (2007) 54–61
[82] H. Chigira, M. Kobayashi, A. Maeda, Mouse with photo-plethysmographic surfaces for unobtrusive stress monitoring, in: 2012 IEEE Second International Conference on Consumer Electronics – Berlin (ICCE-Berlin), IEE, 2012, pp. 304–305. doi:http://dx.doi.org/10.1109/ICCE-Berlin.2012.6336529. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6336529>.
[83] N.R. Armando Barreto, Jing Zhai, Y. Gao, Measurement of pupil diameter variations as a physiological indicator of the affective state in a computer user, in: P. John, S. Sollers III, Julian F. Thayer (Eds.), Proceedings of the 44th Annual Rocky Mountain Bioengineering Symposium, vol. 43, ISA, Denver, Colorado, 2007, pp. 146–151.
[84] A. Barreto, J. Zhai, N. Rishe, Y. Gao, Significance of pupil diameter measurements for the assessment of affective state in computer users, in: K. Elleithy (Ed.), Advances and Innovations in Systems, Computing Sciences and Software Engineering, Springer, Netherlands, Dordrecht, 2007, pp. 59–64. doi:http://dx.doi.org/10.1007/978-1-4020-6264-3, <http://www.springerlink.com/index/10.1007/978-1-4020-6264-3>.
[85] K. Sakamoto, S. Aoyama, S. Asahara, Relationship between emotional state and pupil diameter variability under various types of workload stress, in: B.-T. Karsh (Ed.), Ergonomics and Health Aspects of Work with Computers, Lecture Notes in Computer Science, vol. 5624, Springer, Berlin, Heidelberg, 2009, pp. 177–185. doi:http://dx.doi.org/10.1007/978-3-642-02731-4. <http://www.springerlink.com/index/10.1007/978-3-642-02731-4>.
[86] P. Ren, A. Barreto, J. Huang, Y. Gao, F.R. Ortega, M. Adjouadi, Off-line and on-line stress detection through processing of the pupil diameter signal, Ann. Biomed. Eng. 42 (1) (2014) 162–176, http://dx.doi.org/10.1007/s10439-013-0880-9.
[87] M.E. Jabon, J.N. Bailenson, E. Pontikakis, L. Takayama, C. Nass, Facial expression analysis for predicting unsafe driving behavior, IEEE Pervasive Comput. 10 (4) (2011) 84–95, http://dx.doi.org/10.1109/MPRV.2010.46. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5456355>.
[88] M. Haak, S. Bos, S. Panic, L.J.M. Rothkrantz, Detecting stress using eye blinks and brain activity from EEG signals, in: L. Breitlauch (Ed.), GAMEON, EUROSIS, 2009, pp. 75–82. <http://dblp.uni-trier.de/db/conf/gameon/gameon2009.html#HaakBPR09>.
[89] D. Shastri, M. Papadakis, P. Tsiamyrtzis, B. Bass, I. Pavlidis, Perinasal imaging of physiological stress and its affective potential, IEEE Trans. Affective Compu. 3 (3) (2012) 366–378, http://dx.doi.org/10.1109/T-AFFC.2012.13. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6205729>.
[90] T. Chen, P. Yuen, M. Richardson, G. Liu, Z. She, Detection of psychological stress using a hyperspectral imaging technique, IEEE Transac. Affective Comput 5 (4) (2014) 391–405, http://dx.doi.org/10.1109/TAFFC.2014.2362513. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6919328>.
[91] R.L. Mandryk, C. Epp, M. Lippold, Identifying emotional states using keystroke dynamics, in: Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems – CHI '11, 2011, p. 715. doi:http://dx.doi.org/10.1145/1978942.1979046. <http://dl.acm.org/citation.cfm?doid=1978942.1979046>.
[92] N. Ahmad, A. Szymkowiak, P.a. Campbell, Keystroke dynamics in the pre-touchscreen era, Frontiers Human Neuroscience 7 (December) (2013) 835, http://dx.doi.org/10.3389/fnhum.2013.00835. <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3867681&tool=pmcentrez&rendertype=abstract>.
[93] M. Curtin, C. Tappert, M. Villani, G. Ngo, J. Simone, H.S. Fort, S.-H. Cha, Keystroke biometric recognition on long-text input: a feasibility study, in: Proceedings of Student/Faculty Research Day, 2006, pp. 1–5.
[94] R.L. Mandryk, C. Epp, M. Lippold, Identifying emotional states using keystroke dynamics, in: Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems – CHI '11, 2011, p. 715. doi:http://dx.doi.org/10.1145/1978942.1979046. <http://dl.acm.org/citation.cfm?doid=1978942.1979046>.
[95] A. Kolakowska, A review of emotion recognition methods based on keystroke dynamics and mouse movements, in: 2013 6th International Conference on Human System Interactions (HSI), IEEE, 2013, pp. 548–555. doi:http://dx.doi.org/10.1109/HSI.2013.6577879. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6577879>.
[96] A. Alhothali, Modeling User Affect Using Interaction Events, Ph.D. thesis, University of Waterloo, 2011.
[97] M. Gomes, T. Oliveira, D. Carneiro, P. Novais, Establishing the relationship between personality traits and stress in an intelligent environment, in: M. Ali, J.-S. Pan, S.-M. Chen, M.-F. Horng (Eds.), Modern Advances in Applied Intelligence, Lecture Notes in Computer Science, vol. 8482, Springer International Publishing, Cham, 2014, pp. 378–387. doi:http://dx.doi.org/10.1007/978-3-319-07467-2. <http://link.springer.com/10.1007/978-3-319-07467-2>.
[98] S. Salmeron-Majadas, O.C. Santos, J.G. Boticario, An evaluation of mouse and keyboard interaction indicators towards non-intrusive and low cost affective modeling in an educational context, Proc. Comput. Sci. 35 (2014) 691–700, http://dx.doi.org/10.1016/j.procs.2014.08.151. <http://linkinghub.elsevier.com/retrieve/pii/S1877050914011168>.
[99] R.V. Yampolskiy, V. Govindaraju, Behavioural biometrics: a survey and classification, Int. J. Biometr. 1 (1) (2008) 81, http://dx.doi.org/10.1504/IJBM.2008.018665. <http://www.inderscience.com/link.php?id=18665>.
[100] A. Kapoor, R.W. Picard, Multimodal affect recognition in learning environments, in: Proceedings of the 13th Annual ACM International Conference on Multimedia – MULTIMEDIA '05, 2005, p. 677. doi:http://dx.doi.org/10.1145/1101149.1101300. <http://portal.acm.org/citation.cfm?doid=1101149.1101300>.
[101] B. Arnrich, C. Setz, R. La Marca, G. Tröster, U. Ehlert, What does your chair know about your stress level?, IEEE Transa Inform. Technol. Biomed. 14 (2) (2010) 207–214, http://dx.doi.org/10.1109/TITB.2009.2035498.
[102] K. Dedovic, R. Renwick, N.K. Mahani, V. Engert, S.J. Lupien, J.C. Pruessner, The montreal imaging stress task: using functional imaging to investigate the effects of perceiving and processing psychosocial stress in the human brain, J. Psychiat. Neurosci. 30 (2005) 319–325. <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1197276&tool=pmcentrez&rendertype=abstract>.
[103] D.F. Dinges, R.L. Rider, J. Dorrian, E.L. McGlinchey, N.L. Rogers, Z. Cizman, S.K. Goldenstein, C. Vogler, S. Venkataraman, D.N. Metaxas, Optical computer recognition of facial expressions associated with stress induced by performance demands, in: Aviation Space and Environmental Medicine, vol. 76, 2005.

[104] H. Madokoro, K. Sato, Facial expression spacial charts for describing dynamic diversity of facial expressions, J. Multimedia 7 (4) (2012) 314–324, http://dx.doi.org/10.4304/jmm.7.4.314-324. <http://ojs.academypublisher.com/index.php/jmm/article/view/8027>.
[105] A.V. Boxtel, Facial EMG as a tool for inferring affective states, in: P.Z.A.J. Spink, F. Grieco, O. Krips, L. Loijens, L. Noldus (Eds.), Proceedings of Measuring Behavior 2010, vol. 2010, Noldus Information Technology, Wageningen, The Netherlands, 2010, pp. 104–108.
[106] S. Das, K. Yamada, Evaluating instantaneous psychological stress from emotional composition of a facial expression, J. Adv. Comput. Intell. Intell. Inform. 17 (4) (2013).
[107] M. Hagmueller, E. Rank, G. Kubin, Evaluation of the Human Voice for Indications of Workload Induced Stress in the Aviation Environment, Tech. rep. 18, European Organisation for the Safety of Air Navigation, Brétigny-sur-Orge, France, 2006.
[108] H. Lu, D. Frauendorfer, M. Rabbi, M.S. Mast, G.T. Chittaranjan, A.T. Campbell, D. Gatica-Perez, T. Choudhury, StressSense: detecting stress in unconstrained acoustic environments using smartphones, in: Proceedings of the 2012 ACM Conference on Ubiquitous Computing – UbiComp '12, ACM Press, New York, USA, 2012, p. 351. doi:http://dx.doi.org/10.1145/2370216.2370270. <http://dl.acm.org/citation.cfm?doid=2370216.2370270>.
[109] V.P. Patil, K.K. Nayak, M. Saxena, Voice stress detection, Int. J. Electr. Electron. Comput. Eng. 2 (2) (2013) 148–154. <http://researchtrend.net/ijet21/ijetnew/24VIJAYPATIL.pdf>.
[110] P. Adams, M. Rabbi, T. Rahman, M. Matthews, A. Voida, G. Gay, T. Choudhury, S. Voida, Towards personal stress informatics: comparing minimally invasive techniques for measuring daily stress in the wild, in: Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare, ICST, 2014. doi:http://dx.doi.org/10.4108/icst.pervasivehealth.2014.254959. <http://eudl.eu/doi/10.4108/icst.pervasivehealth.2014.254959>.
[111] G. Demenko, M. Jastrzebska, Analysis of voice stress in call centers conversations, in: Proceedings of the 6th International Conference on Speech Prosody, vol. 1, 2012, pp. 3–6.
[112] A. Muaremi, B. Arnrich, G. Tröster, Towards measuring stress with smartphones and wearable devices during workday and sleep, BioNanoScience 3 (2) (2013) 172–183, http://dx.doi.org/10.1007/s12668-013-0089-2. <http://link.springer.com/10.1007/s12668-013-0089-2>.
[113] A. Aztiria, J.C. Augusto, R. Basagoiti, A. Izaguirre, D.J. Cook, Learning frequent behaviors of the users in intelligent environments, IEEE Trans. Syst. Man, Cybernet.: Syst. 43 (6) (2013) 1265–1278, http://dx.doi.org/10.1109/TSMC.2013.2252892. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6516530>.
[114] S. Rai, X. Hu, Behavior pattern detection for data assimilation in agent-based simulation of smart environments, in: 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT), IEEE, 2013, pp. 171–178. doi:http://dx.doi.org/10.1109/WI-IAT.2013.106. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6690786>.
[115] C.-W. Chen, A. Aztiria, H. Aghajan, Learning human behaviour patterns in work environments, in: CVPR 2011 Workshops, IEEE, 2011, pp. 47–52. doi:http://dx.doi.org/10.1109/CVPRW.2011.5981696. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5981696>.
[116] S.J.O. Malley, R.T. Smith, B.H. Thomas, Data mining office behavioural information from simple sensors, in: Proceedings of the Thirteenth Australasian User Interface Conference – vol. 126, Australian Computer Society, Inc., Melbourne, Australia, 2012, pp. 97–98.
[117] S. Puteh, C. Langensiepen, A. Lotfi, Fuzzy ambient intelligence for intelligent office environments, in: 2012 IEEE International Conference on Fuzzy Systems, IEEE, 2012, pp. 1–6. doi:http://dx.doi.org/10.1109/FUZZ-IEEE.2012.6250771. <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6250771>.
[118] S. Tao, M. Kudo, H. Nonaka, J. Toyama, Person authentication and activities analysis in an office environment using a sensor network, in: R. Wichert, K. Van Laerhoven, J. Gelissen (Eds.), Constructing Ambient Intelligence, Communications in Computer and Information Science, Communications in Computer and Information Science, vol. 277, Springer, Berlin, Heidelberg, 2012, pp. 119–127. doi:http://dx.doi.org/10.1007/978-3-642-31479-7. <http://link.springer.com/10.1007/978-3-642-31479-7>.
[119] N.K. Suryadevara, M. Quazi, S.C. Mukhopadhyay, Smart sensing system for human emotion and behaviour recognition, in: M.K. Kundu, S. Mitra, D. Mazumdar, S.K. Pal (Eds.), Perception and Machine Intelligence, Lecture Notes in Computer Science, vol. 7143, Springer, Berlin, Heidelberg, 2012, pp. 11–22. doi:http://dx.doi.org/10.1007/978-3-642-27387-2. <http://www.springerlink.com/index/10.1007/978-3-642-27387-2>.
[120] J.W. Pennebaker, R.J. Booth, M.E. Francis, Linguistic Inquiry and Word Count (LIWC). <http://www.liwc.net/>.
[121] Harvard General Inquirer. <http://www.wjh.harvard.edu/inquirer/>.
[122] Lexalytics, Semantria. <https://semantria.com/>.
[123] SentiStrength. <http://sentistrength.wlv.ac.uk/>.
[124] Synesketch: Free Open-Source Software for Textual Emotion Recognition and Visualization. <http://synesketch.krcadinac.com/>.
[125] M. Taboada, J. Brooke, M. Tofiloski, K. Voll, M. Stede, Lexicon-based methods for sentiment analysis, Comput. Linguist. 37 (2) (2011) 267–307, http://dx.doi.org/10.1162/COLI_a_00049.
[126] M.D. Choudhury, M. Gamon, Predicting depression via social media, ... and Social Media 2. <http://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/viewFile/6124/6351>.
[127] M. Park, C. Cha, M. Cha, Depressive moods of users portrayed in twitter, in: Proc. of the ACM SIGKDD Workshop on .... <http://wan.poly.edu/KDD2012/forms/workshop/HI-KDD12/doc/paper_16.pdf>.
[128] S. Saleem, R. Prasad, S. Vitaladevuni, M. Pacula, M. Crystal, B. Marx, D. Sloan, J. Vasterling, T. Speroff, Automatic detection of psychological distress indicators and severity assessment from online forum posts, Proc. COLING 2012 (5) (2012) 2375–2388.
[129] M. Ester, H.-p. Kriegel, J. Sander, X. Xu, A density-based algorithm for discovering clusters in large spatial databases with noise, in: Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining (KDD-96), 1996.
[130] D. Lahat, C. Jutten, Challenges in multimodal data fusion, in: 2014 Proceedings of the 22nd European Signal Processing Conference (EUSIPCO), IEEE, Lisbon, 2014, pp. 101–105.
[131] P.G. Zimmermann, P. Gomez, B. Danuser, S.G. Schär, Extending usability: putting affect into the user-experience, in: The 2nd COST294-MAUSE International Open Workshop, 2006, pp. 27–32.
[132] A.C. Aguiar, M. Kaiseler, H. Meinedo, T.E. Abrudan, P.R. Almeida, Speech stress assessment using physiological and psychological measures, in: Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication – UbiComp '13 Adjunct, 2013, pp. 921–930. doi:http://dx.doi.org/10.1145/2494091.2497346. <http://dl.acm.org/citation.cfm?doid=2494091.2497346>.
[133] L. Schwabe, O.T. Wolf, Stress prompts habit behavior in humans, J. Neurosci.: Official J. Soc. Neurosci. 29 (22) (2009) 7191–7198, http://dx.doi.org/10.1523/JNEUROSCI.0979-09.2009. <http://www.ncbi.nlm.nih.gov/pubmed/19494141>.
[134] J.C. Wyatt, J.L.Y. Liu, Basic concepts in medical informatics, J. Epidemiol. Commun. Health 56 (11) (2002) 808–812, http://dx.doi.org/10.1136/jech.56.11.808.
[135] BIOPAC Systems, BIOPAC Systems Inc. <www.biopac.com>.
[136] Thought Technology Ltd., FlexComp System with/BioGraph Infiniti Software – T7555M. <http://thoughttechnology.com/index.php/flexcomp-system-with-biograph-infiniti-software-t7555m.html>.
[137] Trans Cranial Technologies Ltd., 10/20 System Positioning Manual, Tech. rep., 2012. <www.trans-cranial.com>.
[138] U. Lindemann, A. Hock, M. Stuber, W. Keck, C. Becker, Evaluation of a fall detector based on accelerometers: a pilot study, Med. Biol. Eng. Comput. 43 (5) (2005) 548–551, http://dx.doi.org/10.1007/BF02351026.
[139] P. Zappi, C. Lombriser, L. Benini, G. Tröster, Collecting datasets from ambient intelligence environments, in: K. Curran (Ed.), Innovative Applications of Ambient Intelligence: Advances in Smart Systems, IGI Global, 2012. p. 332.
[140] R. Khusainov, D. Azzi, I.E. Achumba, S.D. Bersch, Real-time human ambulation, activity, and physiological monitoring: taxonomy of issues, techniques, applications, challenges and limitations, Sensors (Basel, Switzerland) 13 (10) (2013) 12852–12902, http://dx.doi.org/10.3390/s131012852.
[141] B. Arnrich, C. Kappeler-setz, J. Schumm, G. Tröster, Design, implementation and evaluation of a multimodal sensor system integrated into an airplane seat, Sensor Fusion – Foundation and Applications (2010) 159.
[142] H. Borotschnig, L. Paletta, M. Prantl, A. Pinz, Comparison of probabilistic, possibilistic and evidence theoretic fusion schemes for active object recognition, Computing (Vienna/New York) 62 (4) (1999) 293–319, http://dx.doi.org/10.1007/s006070050026.
[143] D. Dubois, H. Prade, Possibility theory and data fusion in poorly informed environments, 1994. doi:http://dx.doi.org/10.1016/0967-0661(94)90346-8.
[144] M.C. Florea, A.-L. Jousselme, É. Bossé, Fusion of imperfect information in the unified framework of random sets theory, Tech. rep., Defence R&D Canada, Valcartier, DRDC Valcartier TR 2003-319, 2007.
[145] I. Van Mechelen, A.K. Smilde, A generic linked-mode decomposition model for data fusion, Chemometr. Intell. Lab. Syst. 104 (1) (2010) 83–94, http://dx.doi.org/10.1016/j.chemolab.2010.04.012.
[146] R.R. Yager, On the dempster-shafer framework and new combination rules, 1987. doi:http://dx.doi.org/10.1016/0020-0255(87)90007-7.
[147] P. Smets, Combination of evidence in the transferable belief model, IEEE Trans. Pattern Anal. Machine Intell. 12 (5) (1990) 447–458, http://dx.doi.org/10.1109/34.55104.
[148] J. Dezert, Combination of paradoxical sources of information within the neutrosophic framework, in: Proceedings of the First International Conference on Neutrosophy, Neutrosophic Logic, Neutrosophic Set, Neutrosophic Probability and Statistics, University of New Mexico, Albuquerque, NM, USA, 2002, pp. 22–49. doi:10.1.1.70.6441.
[149] B. Khaleghi, A. Khamis, F.O. Karray, S.N. Razavi, Multisensor data fusion: a review of the state-of-the-art, Inform. Fusion 14 (1) (2013) 28–44, http://dx.doi.org/10.1016/j.inffus.2011.08.001. <http://dx.doi.org/10.1016/j.inffus.2011.08.001>.
[150] M.D. Bugdol, A.W. Mitas, Multimodal biometric system combining ECG and sound signals, Pattern Recogn. Lett. 38 (2014) 107–112, http://dx.doi.org/10.1016/j.patrec.2013.11.014. <http://linkinghub.elsevier.com/retrieve/pii/S0167865513004583>.

[151] J. Pärkkä, Analysis of Personal Health Monitoring Data for Physical Activity Recognition and Assessment of Energy Expenditure, Mental Load and Stress, Ph.D. thesis, Tampere University of Technology, Finland, 2011.
[152] A. Arauzo-Azofra, J.L. Aznarte, J.M. Benítez, Empirical study of feature selection methods based on individual feature evaluation for classification problems, Expert Syst. Appl. 38 (7) (2011) 8170–8177, http://dx.doi.org/10.1016/j.eswa.2010.12.160.
[153] O. Postolache, P.S. Girão, E. Pinheiro, G. Postolache, Unobtrusive and non-invasive sensing solutions for on-line physiological parameters monitoring, Lecture Notes in Electrical Engineering 75 LNEE, 2010, pp. 277–314. doi:http://dx.doi.org/10.1007/978-3-642-15687-8-15.
[154] C.M. Yang, C.C. Wu, C.M. Chou, C.W. Yang, Textile-based breath-sensing belt, in: ICCE 2010 – 2010 Digest of Technical Papers International Conference on Consumer Electronics, 2010, pp. 11–12. doi:http://dx.doi.org/10.1109/ICCE.2010.5418950.
[155] B. Maric, A. Kaan, A. Ignaszewski, S.A. Lear, A systematic review of telemonitoring technologies in heart failure, Eur. J. Heart Failure 11 (5) (2009) 506–517, http://dx.doi.org/10.1093/eurjhf/hfp036.
[156] W.H. Fissell, A.J. Fleischman, H.D. Humes, S. Roy, Development of continuous implantable renal replacement: past and future, 2007. doi:http://dx.doi.org/10.1016/j.trsl.2007.06.001.
[157] M. Okubo, Y. Imai, T. Ishikawa, T. Hayasaka, S. Ueno, T. Yamaguchi, Development of automatic respiration monitoring for home-care patients of respiratory diseases with therapeutic aids, in: IFMBE Proceedings, vol. 22, 2008, pp. 1117–1120. doi:http://dx.doi.org/10.1007/978-3-540-89208-3_267.
[158] B. Guerci, P. Böhme, C. Halter, C. Bourgeois, Capteurs de glucose et mesure continue du glucose, 2010. doi:http://dx.doi.org/10.1016/S1957-2557(10)70032-8.
[159] R. Islam, S.I. Ahamed, N. Talukder, I. Obermiller, Usability of mobile computing technologies, in: Third Symposium of the Workgroup Human–Computer Interaction and Usability Engineering of the Austrian Computer Society, USAB 2007 Graz, Austria, November, 22, 2007, Proceedings, 2007, pp. 227–240. doi:http://dx.doi.org/10.1007/978-3-540-76805-0_19.
[160] U. Anliker, J.A. Ward, P. Lukowicz, G. Tröster, F. Dolveck, M. Baer, F. Keita, E.B. Schenker, F. Catarsi, L. Coluccini, A. Belardinelli, D. Shklarski, M. Alon, E. Hirt, R. Schmid, M. Vuskovic, AMON: a wearable multiparameter medical monitoring and alert system, IEEE Trans. Inform. Technol. Biomed. 8 (4) (2004) 415–427, http://dx.doi.org/10.1109/TITB.2004.837888.
[161] H. Miwa, S.-i. Sasahara, T. Matsui, Roll-over detection and sleep quality measurement using a wearable sensor., in: Conference Proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society, Conference 2007, 2007, pp. 1507–1510. doi:http://dx.doi.org/10.1109/IEMBS.2007.4352587.
[162] S.J.M. Bamberg, A.Y. Benbasat, D.M. Scarborough, D.E. Krebs, J.A. Paradiso, Gait analysis using a shoe-integrated wireless sensor system, IEEE Trans. Inform. Technol. Biomed. 12 (4) (2008) 413–423, http://dx.doi.org/10.1109/TITB.2007.899493.
[163] T. Giorgino, P. Tormene, F. Lorussi, D. De Rossi, S. Quaglini, Sensor evaluation for wearable strain gauges in neurological rehabilitation, IEEE Trans. Neural Syst. Rehabil. Eng. 17 (4) (2009) 409–415, http://dx.doi.org/10.1109/TNSRE.2009.2019584.
[164] R.D. Beach, F. Moussy, Totally implantable real-time in vivo video telemetry monitoring system for implant biocompatibility studies, IEEE Trans. Instrument. Measurement 50 (3) (2001) 716–723, http://dx.doi.org/10.1109/19.930445.
[165] A. Chaudhary, M.J. McShane, R. Srivastava, Glucose response of dissolved-core alginate microspheres: towards a continuous glucose biosensor, Analyst 135 (10) (2010) 2620–2628, http://dx.doi.org/10.1039/c0an00109k.
[166] B. Kellihan, T.J. Doty, W.D. Hairston, J. Canady, K.W. Whitaker, C.-t. Lin, T.-p. Jung, K. Mcdowell, A real-world neuroimaging system to evaluate stress, in: D.D. Schmorrow, C.M. Fidopiastis (Eds.), Foundations of Augmented Cognition, Lecture Notes in Computer Science, vol. 8027, Springer, Berlin, Heidelberg, 2013, pp. 316–325. doi:http://dx.doi.org/10.1007/978-3-642-39454-6. <http://link.springer.com/10.1007/978-3-642-39454-6>.
[167] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, E. Campo, Smart wearable systems: current status and future challenges, Artif. Intell. Med. 56 (3) (2012) 137–156, http://dx.doi.org/10.1016/j.artmed.2012.09.003. <http://dx.doi.org/10.1016/j.artmed.2012.09.003>.
[168] K.-h. Chang, D. Fisher, J. Canny, B. Hartmann, How's my mood and stress? an efficient speech analysis library for unobtrusive monitoring on mobile phones, in: BODYNETS 2011, November, 2011, pp. 71–77. doi:http://dx.doi.org/10.4108/icst.bodynets.2011.247079.
[169] G. Acampora, D.J. Cook, P. Rashidi, A.V. Vasilakos, A survey on ambient intelligence in health care, in: Proc IEEE Inst Electr Electron Eng., vol. 101, 2013, pp. 2470–2494. Available from: arXiv:NIHMS150003, doi:http://dx.doi.org/10.1109/JPROC.2013.2262913.
[170] A.F. Shah, A.R. Sukumar, P.B. Anto, Automatic stress detection from speech by using support vector machines and discrete wavelet transforms, in: International Conference on VLSI Design and Communication Systems (ICVLSICOM), Chennai, India, 2010.
[171] L.C. Molina, L. Belanche, À. Nebot, Feature selection algorithms: a survey and experimental evaluation, in: Proceedings of the 2002 IEEE International Conference on Data Mining, 2002 (ICDM 2002), 2002, pp. 306–313. doi:http://dx.doi.org/10.1109/ICDM.2002.1183917.
[172] Y. Chen, Y. Li, X.-Q. Cheng, L. Guo, Survey and taxonomy of feature selection algorithms in intrusion detection system, Inform. Security Cryptol. 4318 (2006) 153–167, http://dx.doi.org/10.1007/11937807_13. http://cat.inist.fr/?aModele=afficheN&cpsidt=19937831. http://link.springer.com/chapter/10.1007/11937807_13.
[173] S. Vanaja, K. Ramesh Kumar, Analysis of feature selection algorithms on classification: a survey, Int. J. Comput. Appl. 96 (17) (2014) 29–35, http://dx.doi.org/10.5120/16888-6910. <http://research.ijcaonline.org/volume96/number17/pxc3896910.pdf>.
[174] S.B. Kotsiantis, I.D. Zaharakis, P.E. Pintelas, Machine learning: a review of classification and combining techniques, Artif. Intell. Rev. 26 (3) (2006) 159–190, http://dx.doi.org/10.1007/s10462-007-9052-3.
[175] I. Yoo, P. Alafaireet, M. Marinov, K. Pena-Hernandez, R. Gopidi, J.F. Chang, L. Hua, Data mining in healthcare and biomedicine: a survey of the literature, J. Med. Syst. 36 (4) (2012) 2431–2448, http://dx.doi.org/10.1007/s10916-011-9710-5.
[176] I.H. Witten, E. Frank, M. a. Hall, Data Mining: Practical Machine Learning Tools and Techniques, 2011. <http://books.google.com/books?id=bDtLM8CODsQC&pgis=1>.
[177] Z. Ghahramani, An introduction to hidden Markov models and Bayesian networks, Int. J. Pattern Recogn. Artif. Intell. 15 (1) (2001) 9–42.
[178] V. Guralnik, K.Z. Haigh, Learning models of human behaviour with sequential patterns, in: Proceedings of the AAAI-02 workshop "Automation as Caregiver", 2002, pp. 24–30.
[179] A. Aztiria, G. Farhadi, H. Aghajan, User behavior shift detection in ambient assisted living environments, J. Med. Internet Res. 15 (6). doi:http://dx.doi.org/10.2196/mhealth.2536.
[180] European Data Format. <http://www.edfplus.info/>.
[181] B. Kemp, J. Olivan, European data format 'plus' (EDF+), an EDF alike standard format for the exchange of physiological data, Clin. Neurophysiol. 114 (9) (2003) 1755–1761, http://dx.doi.org/10.1016/S1388-2457(03)00123-8.
[182] A. Schlögl, O. Filz, H. Ramoser, G. Pfurtscheller, GDF – A general dataformat for biosignals Version 1.25, Tech. rep., 2005. Available from: arXiv:0608052. <http://arxiv.org/abs/cs/0608052>.
[183] ISO 11073-91064:2009. <http://www.iso.org/iso/catalogue_detail.htm?csnumber=46493>.
[184] DICOM Digital Imaging and Communications in Medicine. <http://medical.nema.org/standard.html>.
[185] HL7 annotated ECG. <http://www.hl7.org/participate/tool-sandresources.cfm>.
[186] SNOMED CT. <http://www.ihtsdo.org/snomed-ct>.
[187] LOINC from Regenstrief. <https://loinc.org/>.
[188] J.V. Hoof, H.D. Kort, P. Markopoulos, M. Soede, Ambient intelligence, ethics and privacy, Gerontechnology 6 (3). doi:http://dx.doi.org/10.4017/gt.2007.06.03.005.00.
[189] E. Steel, A. Dembosky, Health apps run into privacy snags, 2013. <http://www.ft.com/cms/s/0/b709cf4a-12dd-11e3-a05e-00144feabdc0.html#axzz3k8iFCKaW>.
[190] M. Laszlo, S. Mukherjee, Minimum spanning tree partitioning algorithm for microaggregation, IEEE Trans. Knowl. Data Eng. 17. doi:10.1.1.113.6338.
[191] J.W.J. Wang, Y.L.Y. Luo, Y.Z.Y. Zhao, J.L.J. Le, A survey on privacy preserving data mining, in: 2009 First International Workshop on Database Technology and Applications. doi:http://dx.doi.org/10.1109/DBTA.2009.147.
[192] A. Manuscript, NIH public access, Changes 29 (6) (2012) 997–1003, http://dx.doi.org/10.1016/j.biotechadv.2011.08.021. Available from: arXiv: NIHMS150003.
[193] European Comission, Green Paper on mobile Health (mHealth), Tech. rep., European Commission, Brussels, 2014. <http://ec.europa.eu/newsroom/dae/document.cfm?doc_id=5147>.
[194] P. Rashidi, A. Mihailidis, A survey on ambient-assisted living tools for older adults, IEEE J. Biomed. Health Inform. 17 (3) (2013) 579–590, http://dx.doi.org/10.1109/JBHI.2012.2234129.
[195] R. Sharp, Lacking regulation, many medical apps questionable at best, Tech. rep., New England Center for Investigative Reporting, 2012.
[196] IEC/DIS 82304-1 Health software – Part 1: General requirements for product safety, Tech. rep., International Organization for Standardization; International Electrotechnical Commission, 2015. <http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=59543>.
[197] J.A. Brebner, E.M. Brebner, H. Ruddick-Bracken, Experience-based guidelines for the implementation of telemedicine services, J. Telemed. Telecare 11 (Suppl. 1) (2005) 3–5, http://dx.doi.org/10.1258/1357633054461778.
[198] A. Tinker, P. Lansley, Introducing assistive technology into the existing homes of older people: feasibility, acceptability, costs and outcomes, J. Telemed. Telecare 11 (Suppl. 1) (2005) 1–3, http://dx.doi.org/10.1258/1357633054461787.
[199] T.H. Malasanos, J.B. Burlingame, L. Youngblade, B.D. Patel, A.B. Muir, Improved access to subspecialist diabetes care by telemedicine: cost savings and care measures in the first two years of the FITE diabetes project, J. Telemed. Telecare 11 (Suppl. 1) (2005) 74–76, http://dx.doi.org/10.1258/1357633054461624.
[200] T.H.F. Broens, R.M.H.A. Huis in't Veld, M.M.R. Vollenbroek-Hutten, H.J. Hermens, A.T. van Halteren, L.J.M. Nieuwenhuis, Determinants of successful telemedicine implementations: a literature study, J. Telemed. Telecare 13 (6) (2007) 303–309, http://dx.doi.org/10.1258/135763307781644951.
[201] C.A. Kavamoto, C.L. Wen, L.R. Battistella, G.M. Böhm, A Brazilian model of distance education in physical medicine and rehabilitation based on

videoconferencing and Internet learning, J. Telemed. Telecare 11 (Suppl. 1) (2005) 80–82, http://dx.doi.org/10.1258/1357633054461949.

[202] I.H.M. Aas, J.T. Geitung, Teleradiology and picture archiving and communications systems: changed pattern of communication between clinicians and radiologists, J. Telemed. Telecare 11 (Suppl. 1) (2005) 20–22, http://dx.doi.org/10.1258/1357633054461589.

[203] J. Barlow, S. Bayer, B. Castleton, R. Curry, Meeting government objectives for telecare in moving from local implementation to mainstream services, J. Telemed. Telecare 11 (Suppl. 1) (2005) 49–51, http://dx.doi.org/10.1258/1357633054461723.

[204] A.S. Hansen, Guidelines on Minimum/Non-Exhaustive Patient Summary Dataset for Electronic Exchange in Accordance With the Cross-Border Directive 2011/24/Eu, Tech. rep. November, European Commission, 2013. <http://ec.europa.eu/health/ehealth/docs/guidelines_patient_summary_en.pdf>.