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► To cite this version:

Iris Mezieres, Abir Gorrab, Rébecca Deneckère, Nourhène Ben Rabah, Bénédicte Le Grand. A Systematic Literature Review on Affective Computing Techniques for Workplace Stress Detection - Challenges, Future Directions, from Data Collection to Stress Detection. International Conference on Computer Communication and the Internet (ICCCI), Leipzig University, Sep 2024, Leipzig, Germany, France. hal-04706465

HAL Id: hal-04706465

<https://hal.science/hal-04706465v1>

Submitted on 23 Sep 2024

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A Systematic Literature Review on Affective Computing Techniques for Workplace Stress Detection

Challenges, Future Directions, from Data Collection to Stress Detection

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Abstract. In a world where work significantly impacts daily life, its influence on well-being is undeniable. The prevalence of stress at work has gained an increased attention due to its profound effects on both individual health and corporate performance. Addressing and detecting stress has become an essential challenge in fostering a healthy work environment. Technological innovations, especially in the field of affective computing, which involves various IT resources for analyzing human behavior and emotions, offer promising solutions for measuring employee stress. This paper provides a Systematic Literature Review (SLR) focusing on the existing scientific research in stress at work assessment using affective computing technologies. What distinguishes our work from others is that we deeply focus on each phase of the stress quantification process. We start by reviewing application contexts, before detailing the data collection process, including data sources and collection devices. We then highlight data analysis techniques used in the literature. Finally, we emphasize the challenges discussed by researchers during their work and give insight into future work.

Keywords: Affective Computing, Stress, Workplace, SLR.

1 Introduction

Stress is a natural response of the human body to a feeling of physical, or mental tension or anxiety to enable rapid reaction [2]. However, in the workplace where life is -generally- not at risk, stress has counterproductive consequences. The European Agency for Safety and Health at Work (EU-OSHA)¹ reports that 51% of European workers consider stress a common workplace issue. Despite the consequences on health, such as professional burnout or illnesses, according to the European ESENER

¹ EU-OSHA Homepage, <https://osha.europa.eu/fr>. Accessed 10 Feb 2024

survey², only 34% of continental businesses had adopted an action plan to prevent stress at work in 2019. Identifying stress indicators and allowing proactive intervention significantly increases employees' commitment, job satisfaction, and loyalty, enhancing their productivity [3]. Affective computing may help in this regard, by gathering data for emotion identification and analysis with devices such as smartwatches, phones, or webcams [5]. Data types vary from physiological (heart rate), and physical (body movements) to behavioral characteristics. Adopting affective computing seems promising but some challenges must be addressed for a secure and successful application in real-world environments. In this work, we propose an SLR to answer the following research issue: '*How are affective computing technologies used to improve the measurement of employee stress at work?*'

We first provide background information about causes and consequences of stress at work, and related works in Section 2, before detailing our methodology for this SLR in Section 3. In Section 4, we present the results of our literature review and then discuss the challenges associated with this research question in Section 5. Finally, we draw our conclusions in Section 6.

2 Background and Related Works

In this section, we start by presenting a background on stress at work: its causes and consequences, before discussing related works and initiating our contributions.

2.1 Stress at Work

Causes. We propose in Fig.1 a classification of the causes of stress at work, which may vary according to individuals, their personalities, histories, or perceptions.

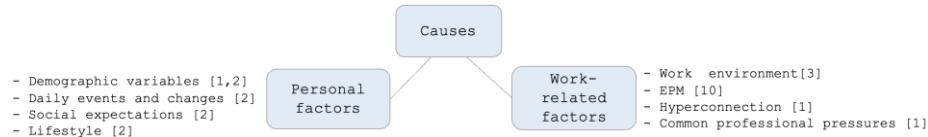


Fig. 1. Classification of Stress at Work Causes.

First, there are several *personal factors* [2], including *demographic variables* such as age, gender, education, or nationality. For instance, women tend to be more affected by stress due to evolutionary differences in neurobiology and hormones [1]. Another personal factor is *lifestyle*, such as lack of physical activity or consumption of alcohol or drugs. *Daily events and changes* can also influence stress, such as relationships with friends or colleagues, family problems, the death of a loved one, etc. Finally, there are demands and *expectations of society*, impacting people differently depending to their personalities.

² ESENER Homepage, <https://osha.europa.eu/fr/facts-and-figures/esener>. Accessed 10 Feb 2024.

Next, we find a set of *work-related factors*. What happens in the *work environment* greatly affects our emotions and feelings. Noise or over-illumination may impact our daily lives even outside of work [3]. *Hyperconnection* also makes it challenging to completely detach from work [1]. *Electronic Performance Monitoring (EPM)* systems provide managers with indicators of employees’ activity (e.g., work pace, connection and disconnection time). The authors of [10] report that these tools increase stress for 81% of employees. Finally, we identified *common professional pressure* as potential causes of stress, such high workload, tight deadlines, long working hours, low salary, and unattainable goals [1].

Consequences. We classified the consequences of stress at work in Fig.2. On the *Personal level*, we note that both mental and physical health may be impacted.

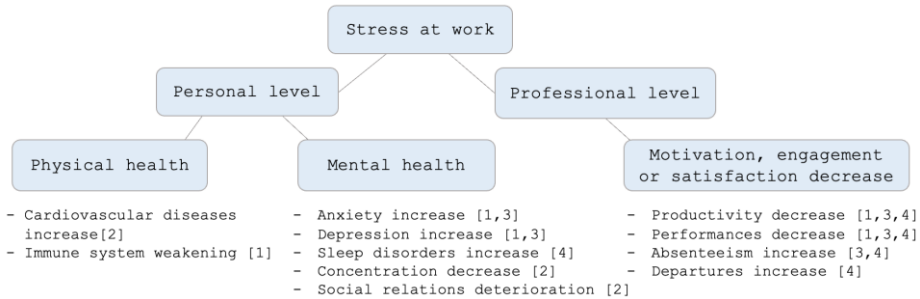


Fig. 2. Classification of Stress at Work Consequences.

Stress also has repercussions on a professional level, through its impact on motivation, engagement, and satisfaction. This results in significant financial losses for companies. Recent studies estimate stress at work to cost the United States more than 300 billion dollars, due to absenteeism, accidents, and reduced productivity³. All of this underscores the need for organizations to prevent, or at least recognize and manage employee stress, to foster a healthy -and therefore constructive- work environment.

2.2 Related Works

Other works have studied the existing literature on stress measurement in professional contexts using affective computing [3, 5, 8, 9]. In [3], the authors highlighted the evolution of methods used to measure the stress of workers. They also compared existing solutions based on cost and privacy impact. In the same context, authors of [5] focused on identifying how affective computing technologies could be used to improve workers’ daily lives. Furthermore, authors of [9] conducted a systematic literature review by identifying the way wearable devices could be used in the workplace for stress measurement. They aimed at determining sensors that could be used, their eventual

³ The American Institute of Stress <https://www.stress.org/workplace-stress>. Accessed 1 March 2024

contributions, and the challenges arising from them. Moreover, authors of [8] studied the way wearable devices and phones could be used to detect stress at work, in education, and transport. They attempted to analyze challenges related to data collection and how contexts could impact the stress measure process. These existing works present some specificities. Some works focus on measuring stress at work [3, 8, 9] while few other works assess stress and emotional states in different aspects of daily life [7]. Some of them focus specifically on studying the use of wearable devices to measure stress [9], while others investigate solutions [3, 7]. In our work, we followed a rigorous research protocol and carefully collected and analyzed research articles to conduct a systematic literature review dedicated to stress assessment at work, using affective computing technologies. What distinguishes our work from others is that we deeply focus on each phase of the stress quantification process. We start by reviewing application contexts, before detailing the data collection process, including data sources and collection devices. We then highlight data analysis techniques used in the literature. Furthermore, we emphasize the challenges discussed by researchers during their work and give insight into future work.

3 Systematic Research Papers Collection Methodology

A SLR [6] is a scientific method employed to investigate a precisely defined issue. It entails employing well-defined methods to select a body of scientific papers sharing a common theme, conducting an in-depth analysis, extracting pertinent information, and synthesizing these findings to address the initial research question comprehensively.

Research Questions. We have structured our initial research issue into 4 Research Questions (RQ):

- **RQ1:** In which contexts is affective computing used to assess stress at work?
- **RQ2:** What data collection methods are used to assess stress at work?
- **RQ3:** How is collected data analyzed?
- **RQ4:** What are the challenges related to the use of affective computing to measure stress at work and how are they addressed in existing works?

Search Query. The following search query was executed on the Scopus library: (“affective computing” OR “sentiment analysis” OR “emotion recognition” OR “artificial intelligence” OR “human-computer interaction” OR “sensors”) AND (workers OR workplace OR offices OR employees OR professionals OR company OR enterprise) AND stress.

Papers Selection. Fig.3. illustrates the steps of the selection process among the 162 papers retrieved automatically at step 1. We note that N refers to the number of papers retained at each step.

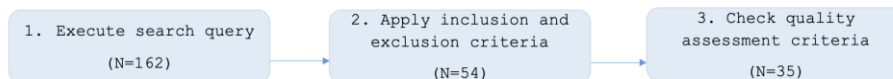


Fig.3. Scientific Papers Selection Process.

We applied *inclusion and exclusion criteria* in step 2. Our Inclusion criteria are: (a) Paper proposing a solution to measure employees' stress at work, using affective computing technologies, (b) Paper published after 2018 (to focus on recent studies), and (c) Paper accessible online. Our exclusion criteria are: (a) Paper not written in English, and (b) Paper not peer-reviewed (such as abstract, poster, proposal, technical report, thesis). We obtained 54 papers after this first selection. At step 3, the 54 remaining papers were checked against the following *quality assessment criteria*: (a) The way data is collected and analyzed is clearly described (yes/no/partially), (b) The context of the study is defined (yes/no/partially), and (c) The study evaluates the performance of the proposed solution (yes/no). Each "yes" is assigned a score of 1, "no" a score of 0 and "partially" a score of 0,5. Papers that scored less than 2 were excluded, resulting in 35 papers for the SLR.

4 SLR Results

4.1 RQ1: Which Context for Stress at Work Assessment?

Table 1 shows that most research works for stress assessment at work using affective computing took place in a static activity context (25 papers), among which 24 in an office. Only 7 papers reported experiments in dynamic environments such as healthcare, industry, or emergency services, while 3 papers on our corpus did not specify the work context.

Table 1. Applications Domains.

	Applications domain	Example of references
Static 25 sources	Office	[16] [20] [35]
	Customer service	[37]
Dynamic 7 sources	Healthcare – paramedical	[24] [30] [31]
	Industry	[14] [33] [42]
	Security - Emergency services	[27]

4.2 RQ2: Which Method of Data Collection for Stress Assessment?

A categorization of collected **data sources** is proposed in Table 2.

Table 2. Collected Data Sources.

Data type		References
Physiological data	Nervous system	[13,26]
	Respiratory and circulatory system	[14, 17, 19, 21, 24, 26, 27, 30, 31, 34, 38, 40, 43, 45]
	Integumentary system	[14, 15, 22, 24, 27, 29, 32, 38, 40, 43, 45]
Physical data	Body movements	[11, 17, 20, 28, 36, 45]
	Facial expressions and eye blinks	[18, 19, 26, 33]

Behavioural data	Vocal characteristics and speech like voice pitch and speech content	[26, 30, 37, 40]
	lexical analysis and punctuation usage	[25]
	mouse clicks speed while using a computer	[12, S6, S9]
	<hr/>	
Others	personal data	[S9, 30, 44]
	environmental data	[11, 26, 27, 30, 39, 40, 44]
	work-related data	[11, 19, 21, 39, 44]

Physiological data consists of biometric data, which may be related to the nervous system, the respiratory and circulatory system, or the integumentary system (skin conductance response and skin temperature).

Physical data reflect the movement of a part of an individual's body. We distinguish body and facial movement.

Behavioral data characterize the reactions of an individual to his/her emotions. In the context of workplace stress, this includes voice, writing, or interactions with work tools such as computers or phones.

Other data types may be personal data (gender, age, sleep quality), environmental data (temperature, light intensity), or work-related data (schedule, break number). However, this data remains secondary in these works. We note that physiological data are mostly utilized in our corpus, in 19 papers among 35; 10 papers incorporate physical data, while 8 articles use behavioral data. We also observe that different data types are combined in some works [11, 19, 30, 40], enriching data to be analyzed.

We categorize the **devices** used for data collection into four categories:

a) Sensors worn or manipulated by users, such as smartwatches, glasses, or helmets, capture physiological data [13, 14, 22, 23, 24, 26, 27, 29, 30, 31, 32, 33, 38, 40, 41, 42, 43, 44]. In this category, we can also cite phones [21, 30, 39, 40, 43, 44] that represent a rich information source. **b) Sensors embedded in the office** may be computer peripherals, including computer mouse [12, 15, 16], and keyboards [16], used to measure behavioral data. They may also be office chairs [17, 20, 35]. In [20], chairs contain pressure sensors allowing them to measure body movements. **c) Thermal, traditional, and depth-sensing cameras** may also be used as information sensors for measuring stress [11, 18, 22, 36]. Furthermore, **d) surveys** [23, 29] allow for gathering information about individuals' well-being through a set of questions that were carefully analyzed. Even if they were used in 19 works, they remain a secondary resource of information and are generally combined with other sensors. We can see that physiological data were the most popular data used in our selected papers, notably collected through sensors worn or manipulated by users, being available and easy to use in daily life.

4.3 RQ3: How is Collected Stress-Related Data Analyzed?

Artificial intelligence-based solutions. We distinguish traditional Machine Learning (ML) and Deep Learning (DL) algorithms.

ML-based solutions.

On the one hand, *supervised algorithms* are suitable for labeled data, which allow the model to be trained and then used to make predictions. In several papers selected for the SLR, researchers aim at predicting numerical values, which corresponds to a *regression* problem. For example, authors of [32] propose a predictive model of stress to determine an individual’s emotional state based on physiological data from the previous day. To do this, they use the Random Forest (RF) algorithm, which determines an individual’s well-being level with a value varying from 0 to 100. With an average of the Mean Absolute Error (MAE) of 15, their solution proved to be quite effective. Then, in [35], Linear Regression (LR) is utilized to directly associate a stress level from the variation in heart rate. Other solutions called *classification* algorithms exist to predict categories rather than numerical values. The number of desired categories must be made carefully beforehand as the data must be labelled according to this parameter. In [19], the problem is seen as a binary classification with 2 categories: “low stress” and “high stress”, achieved with a RF algorithm. Similarly, authors of [36] define “normal state” and “stressed state” categories and use a Hidden Markov Model (HMM). Moreover, Support Vector Machine (SVM) is trained in [20] to perform a first classification with “stress” and “no stress” labels, then a second one with “low stress”, “medium stress”, and “high stress” labels. On the other hand, *unsupervised algorithms* are useful to deal with unlabelled data. Among them, K-Means and Gaussian Mixture Modelling (GMM) were used in some papers of the SLR. In [36], the authors highlight the benefits of these methods that do not require labeling the data. However, they are less represented in our corpus of articles.

DL-based solutions. When dealing with images or sounds, ML algorithms cannot be efficiently trained, as they mostly require numerical input data. Thus, researchers resort to DL algorithms. In [37], authors leverage Long-Short-Term-Memory networks (LSTM), which is effective in numerous speech-related applications such as emotion recognition in speech. LSTM belongs to Recurrent Neural Networks (RNN) defined as memory neural networks because the output data depends on both input data and previous states of the network. Furthermore, in [30], the bidirectional variant (Bi-LSTM) is used to enhance stress-related emotion detection in speech. Besides, in [11], the Faster R-CNN algorithm is utilized to extract data from video recordings.

Table 3 summarizes AI algorithms used in SLR papers, considering if they belong to Supervised Learning (Classification or Regression) or Unsupervised Learning (Clustering) algorithms. We note that RF and Decision Tree (DT) algorithms figure in both Supervised Learning categories, as in some works, they were used for classification; and in others, they were utilized for Regression.

Table 3. AI Algorithms used in SLR Papers.

Algorithm type	References
Classification (Supervised Learning)	SVM[11,14,16,17,19,20,24,29,31,42,43], DT[11,16,24,39,42,43], K-Nearest Neighbours (KNN) [11,16,17,24,42], RF [16,19,24,43,44], Multilayer Perceptron (LMP) [19,42,44], LSTM [30,37,44], LR [24,43], Gradient Boosting (XGB) [19], Ridge Classifier [19], Naïve

	Bayes [24], Decision Jungle [34], HMM [36], Neural Network (NN) [24], Elastic Net (EN) [44], AdaBoost [43]
Regression (Supervised Learning)	Linear Regression (LR) [21,35], RF [21,32], Ridge Regression [21], DT [21]
Clustering (Unsupervised Learning)	GMM [45], K-Means [25,45]

Other solutions. ML algorithms require large datasets to be trained, when considering different usage contexts [41]. Few works in our corpus use other solutions. [12] utilizes the Poisson regression model, a statistical prediction model, to assess stress-related data obtained from a computer mouse. Moreover, [27] creates a correspondence table to correlate heart rate and skin galvanic response to a potential level of stress and danger for firefighters. In addition, mathematical algorithms are applied in [41], to discretize the dataset into values ranging from 1 (completely relaxed) to 5 (very stressed), using the Symbolic Aggregate Approximation algorithm, and to detect changes in it utilizing ADaptive WINdowing algorithm.

By studying the distribution of adopted solutions, we can see that AI was the most popular solution, being used in 77% of papers selected for the SLR, even though it requires resources to be implemented, such as the collection of large datasets.

5 RQ4: What Challenges and How are they Addressed?

We dedicate this section to the challenges researchers have identified in our corpus, and to their suggestions to meet them. Most challenges raised using affective computing to measure stress at work are related to *ethics, confidentiality, and security*:

Challenge 1: Ethical Data Collection. Nowadays, international privacy laws exist, which may make data collection challenging [34]. However, it is possible to mitigate ethical and confidentiality issues.

Using Less Sensitive Data. In [19], authors distinguish between “low-level” data characterizing sensitive information such as email or text content, and “high-level” data, corresponding to less sensitive information like the number of emails or the duration of a call. Physiological data or user videos belong to the former category, resulting in significant ethical issues and discomfort among participants due to being observed all day [19]. Therefore, various works collect interaction data with work electronic devices (e.g., phones, computers), which appear less intrusive, besides not requiring the addition of extra sensors for data collection [16]. In the same context, authors of [12] use keyboard strokes as input data. In [30], data extraction is performed from audio recordings to store only the data without the raw audio. Similarly, [S30] retains only metadata related to communication such as voice activity or message length, while discarding raw content, notifications, or audio recordings.

Considering User Preferences. In [19], authors propose considering participants’ preferences regarding the data they would prefer to share. In this context, users prefer to share data collected from mouse activity and keyboard. We then find data collected

from computer usage, wearable sensors, microphones and phones. Finally, we find webcams. These preferences depend on concerned users and their activities.

Challenge 2: Data Anonymization. Various solutions exist to this end. First, it is possible to remove data which directly identifies an individual, such as names or phone numbers [12]. At this stage, it is nearly impossible to correlate the data with a specific individual afterward, but it is possible to add a random and unique identifier, known only by the individual concerned, to maintain this link [40]. Another possibility is to encode the data, i.e., replace information about an individual with identifiers or numerical codes [21, 26, 37, 41], and ensure that this process is irreversible [37]. Furthermore, authors in [21] proposed to label data in order to classify responses into categories. For example, categories like “employee under X years old” and “employee over X years old” does not require storing the precise age of the individual.

Challenge 3: Data Secure Storage. Another crucial issue addressed across various studies concerns data security. Due to the sensitive nature of incoming and outgoing data, it should only be accessible to specific individuals, and intrusions or data breaches should be avoided as much as possible. Two storage methods were proposed in our corpus. *Local storage*, as proposed in [19], conserves data directly on the devices used for data collection and processing. This method significantly decreases the risk of data theft since nothing is transmitted nor made accessible to third parties. Other experiments store data on specialized *remote servers* with considerable processing power. This solution may raise concerns regarding access to data by unauthorized individuals or potential cyberattacks. More secure options exist, where access is only granted to authorized individuals through their local internet connection or a Virtual Private Network (VPN), as seen in [40]. Among these options, [19] investigated users’ perceptions seeing their preferred storage method, showing a preference for local storage, as it allows better data management. In conclusion, the choice depends on user preferences, experiments’ objectives, and the needs of the collection, among other factors.

Challenge 4: Results Accessibility. To communicate data analysis results, two models are commonly used: in the *personal model*, individuals have exclusive access to their results [26]. However, this does not necessarily imply that the model is trained only on data about concerned individuals. Whereas in the *communal model*, the results are visible to a group of individuals, such as a team of colleagues. In this case, the objective is to create a supportive team environment where everyone is aware of the stress experienced by their teammates, allowing them to overcome stress-related issues through discussion or relaxation [23]. In this model, data can still be anonymous, meaning that all results can be accessed without knowing to whom they are associated, but data can easily be attributed to a specific person [35]. Users’ feedbacks reflect mixed opinions [23]. While those who are close to their colleagues are comfortable with sharing such data, some show discomfort. This model is much less used than the personal model, as it may even induce more stress among participants, seeing that it invades privacy [23].

The second category of challenges identified in the literature is related to the *reliability* of affective computing tools, i.e., their ability to produce rigorous and consistent stress assessments.

Challenge 5: Reliable Stress Identification. The proposed models should reliably differentiate between stress and other emotional states. In [23], participants gave their feedback on a stress assessment system, and one of them noted that the system seemed more related to overall mood than to stress specifically.

Challenge 6: Real-Environment Implementation. This challenge highlights the importance of conducting experiments in contexts that are as realistic as possible, or directly in workplace environments. In [22], authors criticized scientific articles employing artificially replicated conditions for stress assessment using affective computing, where users perform standard daily tasks. These tasks may induce significantly higher stress levels than those encountered naturally, which may lead to inaccurate conclusions about the model's effectiveness in measuring stress at work. Besides, during data collection, noise may occur in diverse ways. For example, body movements can cause wearable sensors to shift, causing incorrect physiological data collection. Similarly, environmental noises such as conversations or external sounds may impact the quality of the audio recording. Noise can also arise from the quality of the devices used to collect data [42]. It is almost inevitable, whether in a controlled environment or not [23]. It is essential to control it by applying filters or removing excessively noisy data [31].

6 Conclusion

We performed a systematic literature review in which we reviewed a large body of literature describing how affective computing can be used to assess stress at work. We identified an appropriate collection of scientific papers according to some inclusion/exclusion criteria. Subsequently, we analyzed them revealing four different aspects: Application domains, Data collection, Data analysis, and Challenges. Using affective computing to measure stress at work is promising. However, the challenges characterizing these technologies remain alarming. Results interpretability is typically difficult when using deep learning methods, which is appropriate for facial expression analysis. In our future work, we aim to conduct experiments in a real context using a deep learning algorithm to detect negative emotions (such as stress, and despair) by analyzing facial expressions, in larger populations, to have concrete and efficient solutions for stressed and desperate workers.

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