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Stress Detection Using Physiological Sensors

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Psychologists have studied emotions since the 19th century, but there is still no universally accepted definition of emotions and how they are generated. However, more than a century of research shows that emotions and physiology are related. Many studies employ physiological data such as electrodermal, cardiovascular, and muscular activity to measure participants' affective states, including those related to stress. Other instruments such as questionnaires and scales can be used to assess affective states. However, these cannot be administered to users without interrupting the task they are carrying out, thus affecting their emotions. In addition to the possible biases that can affect any type of self-reporting, the intrinsic ambiguity of describing emotions in writing could undermine such instruments' reliability. Thus, developing systems that can detect stress through physiology is particularly appealing, and not just for experimental studies.

Such systems have many possible real-world applications. For example, they could be used to measure and reduce stress and frustration levels in workers who use computers. They could also help users reach and maintain a certain optimal stress level; for example, those being trained to respond to emergency situations could benefit from personalized and progressive exposure to simulated stressors of increasing magnitude.[1] In all cases, accurate recognition of stress is crucial to the application's success. However, the design and evaluation of a stress-detection system must always consider each physiological signal's strengths and weaknesses as defined by current sensors' technological limitations as well as issues intrinsic to human physiology.

Measuring Stress

In everyday language, stress typically indicates strain caused by physical or psychological pressures at work, at school, or in personal life as well as by one's environment. From this point of view, stress can be seen as a defensive process to protect oneself from potential injury and threats to emotional well-being. Thus, it is not surprising that stress is related to the capacity to adapt and respond to various circumstances. In the psychology literature, anxiety is often defined as a negative emotion related to stress characterized by different physiological responses, e.g., cardiac acceleration and fast, shallow breathing.[2]

The physiological responses related to stress and anxiety are controlled by the *autonomic* *nervous system* (ANS), which regulates important bodily activities including digestion, body temperature, blood pressure, and many aspects of emotional behavior.[3] The ANS is organized into the *sympathetic nervous system* (SNS) and the *parasympathetic nervous system* (PNS). The SNS controls activities that are mobilized during emergency situations, which characterize the fight-or-flight response. The PNS controls the basic functions of rest, repair, and restoration of energy stores (rest-and-digest activity).[3]

Electrodermal activity

Electrodermal activity (EDA) sensors measure changes in the electrical conductivity of the skin surface. Changes in EDA can be produced by various physical and emotional stimuli that trigger variations in sweat-gland activity. Unlike other bodily functions, EDA is controlled exclusively by the SNS,[4] making it an ideal physiological signal for stress measurement. Moreover, current EDA sensors are unobtrusive and allow for reliable signal recordings.

The EDA signal can be split into two different components. *Skin conductance level* (SCL) refers to the *tonic* component of the EDA signal—the electrical conductivity at a given point in time. *Skin conductance response* (SCR) is the *phasic* component of EDA—the amount of EDA change that occurs in response to a given stimulus.[3] SCR usually measures physiological responses to discrete events such as a short and intense burst of noise, whereas SCL is useful for measuring more generalized arousal over a time interval.[4] Many studies have successfully employed SCL and SCR as stress indicators during the presentation of a range of stressful stimuli, showing that these signals are a valuable tool for stress assessment.[4] However, EDA alone cannot provide definitive information about stress and anxiety: other physiological signals or instruments such as self-reports are required to discern between positive and negative high-arousal states.

As an example of EDA application, a user study evaluated the effectiveness of three stress-induction techniques applied to a virtual environment (VE) that reproduced a fire emergency.[1] The first technique augmented the VE with a bar indicating the health of the user's avatar. The second augmented the VE with aversive audio-visual stimuli, including a preset heartbeat sound and a red aura flashing in sync with the user's heartbeat (see Figure 1). In the third technique, the frequency of the audio heartbeat and aura flashes were artificially increased when users were in an anxiety-inducing situation, creating the illusion of a physiological change. Combining EDA with a subjective assessment revealed that the third technique induced the most anxiety in study participants.

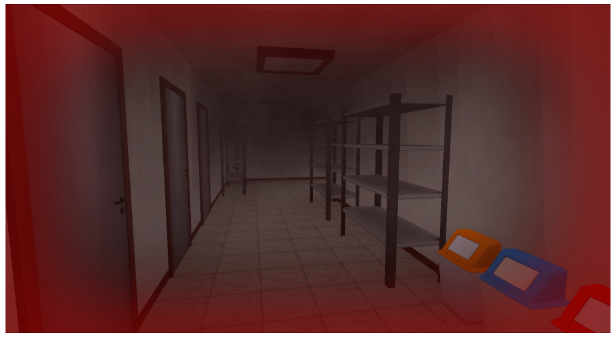

Figure 1. Virtual environment reproducing a fire emergency. A red aura flashes in sync with a user's heartbeat.

Cardiovascular system activity

Cardiovascular system activity can be measured through various physiological signals. In the computer science literature, *blood volume pulse* (BVP) and *electrocardiography* (ECG) are the most frequently employed signals. BVP is related to the amount of blood flowing into the peripheral vessels, such as those in fingers or earlobes, and is generally measured through a photoplethysmograph (PPG). The ECG signal measures the electrical activity of the heart through electrodes placed on the chest. The main disadvantage of measuring heart rate (HR) through a PPG is that the sensor is sensitive to the user's motions. Some PPGs are designed to be placed only on the fingers, so there could be artifacts in BVP signals caused by keyboard, mouse, or game-controller use. In such cases, we use controllers that can be operated with a single hand (for example, the Nintendo Wii Nunchuck), leaving the other hand free for sensor-data recording. ECG electrodes are more robust against motion artifacts, but they must be placed in direct contact with the skin of the user's chest, which is less practical and could be uncomfortable for some users.

HR can easily be calculated from BVP or ECG signals by counting the number of peaks per minute. Increases in HR are generally related to emotional activation and are considered a correlate of arousal[4] and anxiety.[2] Other HR-related features are used as more precise measures of certain characteristics of ANS activity, such as *heart rate variability* (HRV), which describes the variability of HR over time. In general, HRV analysis takes into consideration the frequency power of low-frequency (LF, 0.01−0.08 Hz) and high-frequency (HF, 0.15−0.5 Hz) bands. Increases in LF and in the LF/HF ratio have been related to anxiety.[2] Similar to EDA, cardiovascular activity measures must be associated with other information about users' emotional valence (i.e., the level of perceived pleasantness or unpleasantness of users' emotions) to distinguish between negative high-arousal emotions such as anxiety and positive ones like excitement.

One cardiac feature we employ is *blood volume pulse amplitude* (BVPA), which is the distance between the local maximum and minimum of the BVP signal, and is negatively correlated with arousal.[5] As an example, a study focused on a VE that simulated a full emergency landing and evacuation of a commercial aircraft (see Figure 2).[5] The VE was designed to induce fear—another negative emotion that, similar to anxiety, is related to stress and is characterized, among other physiological effects, by cardiac acceleration and increased EDA.[2] The study included BVPA, paired with EDA and self-report data about perceived fear, to successfully detect emotional arousal and fear in VE users.

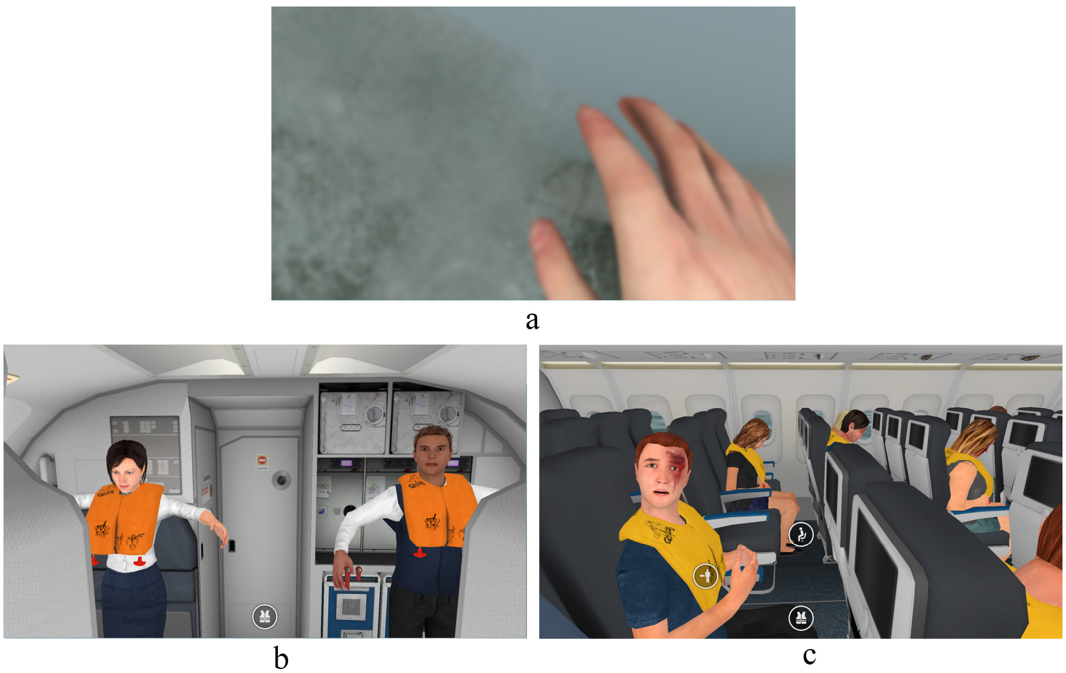

Figure 2. A fear-inducing aircraft emergency simulation. (a) The user is drowning after opening a door below water level. (b) Flight attendants call passengers to the front exits. (c) An injured passenger sits close to the user.

Facial muscle activity

Muscle activity is measured through *electromyography* (EMG), which detects the electrical discharges caused by contractions of muscle fibers. Muscles like zygomaticus major (located in the cheek; responsible for smiling), corrugator supercilii (located in the forehead; responsible for frowning) and orbicularis oculi (located around the eye; responsible for blinking and winking, and contracting when smiling), help distinguish between positive and negative high-arousal emotions related to excitement and stress, respectively.[3]

Muscle activity is measured by placing electrodes on the skin above the considered muscles (surface EMG). Analysis of facial muscle activity can help assess other physiological responses relative to stress, such as the startle response, i.e., a complex of bodily reactions to a strong, rapid, and unexpected stimulus.[4] Among the bodily expressions of the startle response (for example, quickly closing the eyes, accompanied by contracting various muscles), psychophysiology has mostly focused on the eye-blink startle response, which is typically measured as the magnitude of the EMG recorded from the orbicularis oculi region.[4] As with ECG, surface EMG can be cumbersome and uncomfortable for some users, especially in the case of facial EMG. Furthermore, actions like talking or coughing, which involve the activation of various facial muscles, could trigger muscle activity that could mask signal components relevant to stress detection. For this reason, in our studies we ask users not to talk during experiences in VEs, and accurately take note of those users' actions that can require subsequent signal corrections.

As an example of EMG application, we carried out an experiment during which we measured the activity of the corrugator supercilii muscle in two groups of users.[6] The first group navigated a low-stress (see Figure 3a) and a high-stress (see Figure 3b) version of a VE reproducing a multifloor school building, and the second group navigated a low-stress (see Figure 3c) and a high-stress version (see Figure 3d) of a VE reproducing a train station. The high-stress version of the school building simulated a fire emergency, and the high-stress version of the train station involved a terrorist attack scenario. Results showed that in both the school building and the train station VEs, the mean EMG value for the corrugator muscle was higher when users experienced the high-stress version than when they experienced the low-stress version. As expected, these results indicate that more stressful experiences elicited more intense negative emotions.

This study confirms that facial EMG is a valuable instrument for stress detection. However, a potential complication of EMG electrodes must be considered when performing stress detection during experiences with head-mounted displays (HMDs). While HMDs are useful to increase immersion and stress-inducing effects, they can cover the corrugator muscle area of the forehead where electrodes should be placed.

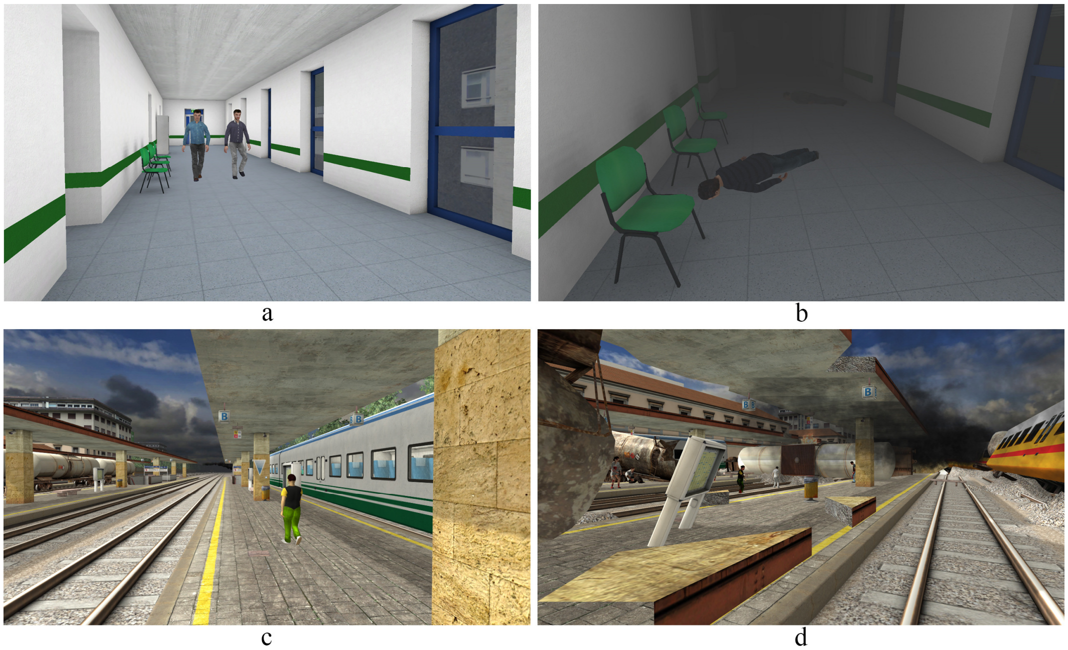

Figure 3. Two virtual environments: (a) low-stress and (b) high-stress versions of a multilevel school building, and (c) low-stress and (d) high-stress versions of a train station.

Respiratory system activity

Respiration is strongly related to cardiovascular system activity, and is mainly influenced by changes between calm and excited states.[7] The respiratory signal can be recorded using an elastic band placed on a user's midsection. More complex setups employ two elastic bands placed on the person's chest and abdomen, because interpersonal differences in breathing lead some individuals to produce more abdominal distension making a belt placed on the chest insensitive to breathing.[8] Using two bands, however, may increase users' discomfort. Stress-related emotions such as anxiety generate faster and shallower breathing.[2] *Respiratory rate* (RR) and *respiratory amplitude* (RA) are employed as measures of SNS activity; RR, however, is regarded as one of the least sensitive metrics for respiratory data analysis.[7] Standard deviations of these measurements, as well as other measurements of their variability, have been frequently used to characterize respiratory variability, which seems to be negatively correlated to anxiety.[8]

Other signals and emerging techniques

Other physiological signals can be employed for stress detection, but are generally less practical than those discussed here. For example, both *electroencephalography* (EEG) and *task-evoked pupillary response* (TEPR)—a measure of changes in pupil diameter—are problematic. Placing EEG sensors is time-consuming and requires accurate skin preparation for optimal detection, including scratching a user's scalp with an abrasive gel and applying conductive paste on the head. Promising research focuses on dry EEG sensors, i.e., sensors that can be placed directly on the scalp without skin preparation, which could be a practical alternative to existing sensors.

However, there are still issues related to users' comfort and the cost of equipment, which could still be too expensive for small laboratories.[9] Moreover, EEG and TEPR recording procedures can require presenting the stimulus a number of times to obtain the average response.[3]

Brain activity analysis techniques that rely on optical sensors such as functional near-infrared spectroscopy (fNIRS) are emerging as alternatives to EEG. fNIRS is a noninvasive imaging method that measures relative changes in cerebral blood flow, which is correlated to localized neuronal activity. Optical techniques have also been proposed to detect stress through thermal video analysis of the face. Stress seems to be correlated with increased blood flow in the forehead and around the eyes, which dissipates convective heat that can be monitored through thermal imaging in real time.

Applications of Automatic Stress-Detection

In recent years, researchers have proposed various systems that use physiological signals to automatically detect stress as well as other emotions such as joy and surprise. Davor Kukolja and his colleagues provide an overview of the most recent and relevant systems, indicating the techniques used to extract and combine physiological features to detect stress and the systems' detection accuracy.[10]

Exposure therapy

Exposure therapy is a technique intended to treat anxiety disorders that involves progressive exposure to the feared object or context to inhibit fear and overcome anxiety related to the object or content. Virtual reality exposure therapy (VRET) has been proposed as an efficient and cost-effective alternative to in-vivo exposure for the treatment of anxiety disorders. For example, VEs that simulate flying on airplanes have been used to treat aviophobia (fear of flying), and combat simulators (such as Virtual Iraq and Virtual Afghanistan) have been used to treat soldiers who suffer from post-traumatic stress disorder. VRET applications could exploit real-time monitoring of affective states in patients with anxiety disorders, providing valuable information to therapists and allowing for a more tailored and personalized treatment—for example, by dynamically adapting the experience to elicit the desired level of stress in patients.

Training

Training supports the acquisition of knowledge, competence, and skills through direct or indirect experience. During emergency training, for example, first responders can learn how to provide medical care by being immersed in VEs that accurately replicate a dangerous environment. Training can also help people develop coping skills to reduce anxiety and maintain an optimal level of performance under stress. This particular method is called stress inoculation training (SIT).

By feeding information back to users about their affective state (biofeedback), applications can enable users to learn how to change their physiological activity to improve their health and performance. Biofeedback is sometimes integrated into serious games for training. As an example, we developed a biofeedback application to influence the affective state and behavior (such as body gestures, facial expressions, and vocal expressions) of a 3D virtual character shown on a screen.[11] The more relaxed the user is, the more relaxed the character is (see Figure 4a); if the user is stressed, the character shows clear signs of stress and cannot complete a task in the game (see Figure 4b). In a similar way, biofeedback has been employed to provide soldiers with explicit feedback about their arousal level when immersed in stress-inducing combat VEs to practice stress-management skills such as tactical breathing—as in, for example, Canada's Immersion and Practice of Arousal Control Training (ImPACT) program.[12]

Biofeedback has also been employed in the treatment of anxiety disorders to support relaxation training by exploiting users' stress levels to control a racing video game (*Relax & Race*; https://itunes.apple.com/us/app/pip-relax-race/id839560263?mt=8) or to affect the appearance of a VE.[13] In the video game, the more relaxed the users are, the faster they race; in the VE, relaxation can reduce the intensity of visual and audio stimuli. As recently shown, biofeedback can also be integrated in training applications for inducing stress instead of promoting relaxation.[1] Dynamic adaptation of VEs through physiology has been proposed to tailor game difficulty in relation to users' stress, helping them maximize engagement: too much of a challenge could increase users' frustration and stress, whereas not enough of a challenge would induce boredom.

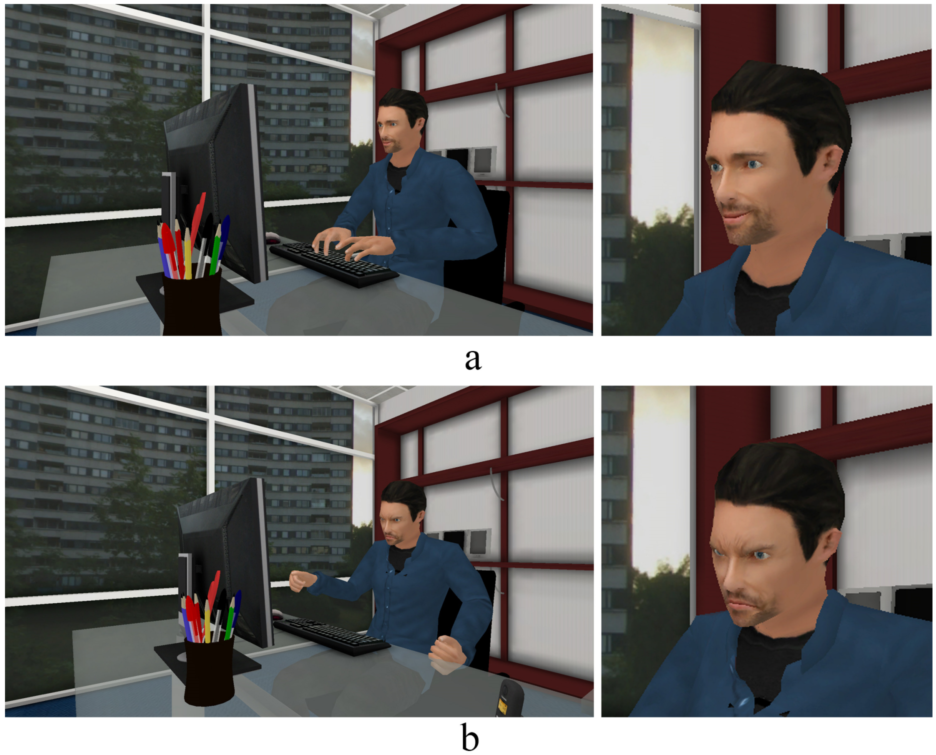

Figure 4. Two affective states of a virtual character employed in our biofeedback application. (a) The character is completely relaxed and working at his desk. (b) The character is stressed and cannot work.

Monitoring worker performance and health

Various studies have observed a relationship between stress and work performance.[14] Systems that automatically detect workers' stress levels could be integrated into workplace computers to dynamically manipulate the state of applications and adapt workload to workers' stress level. Alternatively, these systems could use workers' stress level to provide assistance in the form of suggestions or support. Real-time information about stress level is particularly relevant in emergency situations—for example, stress detection can enhance collaboration among soldiers in military deployments and among first responders after natural disasters. Such applications of stress detection, which are useful in real-life human collaboration, could also be used in emergency training simulations.

Enhanced remote communication

Automatic stress monitoring can be employed to enhance remote communication. Text-, audio-, and video-based applications have been augmented with information about anxiety to enhance nonverbal communication—for example, Conductive Chat (http://affect.media.mit.edu/projects.php?id=749). This approach has been proposed for remote video-mediated assistance applications, which report workers' stress levels to instructors to optimize assistance activity, as well as in distance-learning applications to provide teachers with information about their students' stress level. Stress detection can enhance interactions not only among humans, but also among humans and robots or embodied conversational agents (ECAs).

Limitations and Future Research

Physiological signals such as SCL, HR, and facial EMG can successfully detect a person's stress level, but each physiological sensor has its weaknesses. Researchers are trying to address some of these limitations, such as developing reliable EEG sensors that do not require skin preparation. Further steps, however, are required to make physiological computing applications more practical for everyday use and widely accepted by the general public.

To reach this goal, physiological sensors must be included in objects that people would not hesitate to use. For example, sensors have been added to objects such as PC mice (EDA electrodes) and smartphones (optical sensors for BVP recording). A recent trend is the inclusion of such sensors in wearables, which, unlike other technologies, are designed to be in contact with users all day. Commercial devices such as the Samsung Gear S and the Apple Watch measure users' HR and EDA in real time; although their sensors are currently limited to fitness activity tracking, future and more sophisticated versions of these devices will likely be more accurate, supporting the detection of stress and other emotions.

Issues intrinsic to human physiology have a critical impact on the development and evaluation of automatic stress-detection systems.[15] Very few physiological signals are related to a single emotion; for example, although EDA can be safely considered a correlate of physiological arousal, cardiovascular and respiratory systems are determined by both SNS and ANS activity. Thus, it is complicated to design a physiological computing system that exploits these signals to provide automatic stress detection with consistent accuracy. Signal artifacts caused by user movements might further reduce such accuracy or even prevent real-time stress detection. In addition, people can be stressed for different reasons: for example, stress in a user navigating a VE can be elicited by a malfunctioning controller, a difficult level, or an increase in room temperature as well as by audiovisual stimuli.

To increase stress-detection accuracy, future systems should consider integrating additional physiological measures not yet exploited by physiological computing applications. For example, the eye-blink startle response might be useful, but this response is generally elicited through short bursts of intense white noise, which could distract users from meaningful events in the application. In a previous study, we found that a sound that is contextual to the application being used—for example, an explosion sound in a VE reproducing an emergency (see Figure 3b)—can elicit an eye-blink startle response with a magnitude very close to the one elicited by white noise.[16] Thus, the use of certain contextual sounds could extend the number of computer applications in which eye-blink startle response could be naturally applied.

Novel methodologies are needed to improve the evaluation of physiological computing systems. For example, current studies assess accuracy through confusion matrices, mean error, or mean successful detection rates. A recent experiment we carried out suggests that researchers should also consider the use of placebo conditions, in which a sham instead of a real treatment is administered to participants.[11] A placebo version of a stress-detection system determines users' stress levels pseudorandomly instead of taking into account physiological sensor readings. Unlike traditional control conditions, placebo conditions require users to be unaware of the nature of placebo stress detection. In medical studies, placebo conditions are commonly employed to account for factors such as users' suggestibility. The purpose of the placebo condition is to experimentally evaluate whether the proposed treatment is superior to the sham treatment. For example, an effective biofeedback system for relaxation training should present feedback that users perceive as significantly more accurate with respect to the placebo version, and should allow for easier and faster relaxation training.

Ultimately, stress detection based on physiological sensors can bring real benefits both to researchers, who can obtain a richer and more comprehensive picture of how individuals are affected by technology in user studies, as well as end users, who could benefit from new computer applications that are sensitive to their stress level and provide a more tailored and effective experience. However, designing and bringing such applications to mass markets will strongly depend on progress in sensor technology, data analysis, and evaluation methodologies, aimed at increasing the comfort as well as the accuracy of stress measurement.

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