# Toward Stress Detection During Gameplay: A Survey

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***Abstract*—In day-to-day life, stress can arise due to various factors including work–life demands, external situations, and health issues. Stress becomes a concern when it affects a person's mental health, and sometimes it can even result in other chronic illnesses. Currently, stress-detection studies in the literature are often limited to laboratory studies or to specific situations. However, daily stressors are ongoing, and therefore, detection of stress in everyday life (outside the laboratory environments) is important to improve the wellbeing of individuals. Computer games are entertainment media that can be found in almost every household in the modern society. Statistics show that people spend hours playing computer games daily. The amount of data that gameplay generates and interactivity they provide via various human computer interfaces have a lot of potential in identifying behavior patterns of the players that could assist in the process of stress detection. As such, this survey attempts to identify the extent to which computer games can be used as a medium for stress detection. Toward this end, this survey reviews the existing stress-detection studies, both laboratory techniques as well as the techniques that can be used in a home-based environment. Finally, it summarizes the stress-detection techniques that can be used within games in order to make it an everyday technology that can be used to detect and monitor stress. In addition, it is expected that development of such a technology will be useful in providing objective data to the healthcare professionals for intervention and management. Such a technology is even more required in the current unprecedented situation the world has faced due to the COVID-19 pandemic as it can be developed as a technology to manage mental health issues people are facing due to home isolation.**

***Index Terms*—Affective computing, gameplay, games, games for health, human–computer interaction, machine learning, serious games, stress detection.**

## I. Introduction

PLAYING games is a vastly popular recreational activity all around the world. More than 2.5 billion people across the world play games spending billions of dollars on them [1]. It was revealed that on average players spend more than 6 h/week playing games [2]. Given this popularity and significant amount of time players spend playing games, they have the potential to become a low-cost, everyday technology that can be used to detect and monitor players' mental stress.

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Stress, in day-to-day life can occur due to the imbalance between external demands and the internal ability to meet the demand [3]. Often daily stressors are ongoing and can result in chronic stress that could lead to cardiovascular disease [4], type 2 diabetes [5], as well as anxiety and depression [6], [7]; the latter two are considered to be serious mental health problems.

Detecting and monitoring stress on a daily basis has numerous advantages as it enables one to understand their stress patterns, keep track of their own mental health, apply stress-relieving techniques, and seek professional help as needed. Not only that, a system that can detect and keep track of such daily stress patterns can provide healthcare professionals reliable and objective data that will assist in diagnosis and treatment as needed. This is also particularly useful in the situations like COVID-19 pandemic, because home quarantine and isolation requirements can result in people relying more on computer games as an entertainment media [8] and telehealth for healthcare consultation.

Toward this end, this article surveys the relevant literature in order to understand the research gaps to reach the end goal of employing computer games and gameplay as a mechanism to detect and monitor daily stress that can occur due to various reasons. Most of the stress-detection studies have been conducted in laboratory environments with expensive research grade equipment. On the contrary, to be used as a technology in detecting and monitoring daily stress, the methods need to be cost effective while also giving a reliable performance. Our goal in this article is to investigate the most reliable stress-detection sensors and methods with an aim of identifying the sensors and methods that can be used in a home setting. Thereafter, the sensors and methods that can be used in a gameplay setting will be discussed with an aim of identifying the feasibility of the approach and gaps in terms of performance.

There is no universally accepted definition of stress. In the context of this survey, we adapt the definition of stress from [9], which defines stress as a mismatch between an individual's desired state and the perceived state. It is not within the scope of this review to detect positive stress (eustress—a positive and constructive response to a stressor) or differentiate between positive and negative stress [10].

It has been shown that stress responses are specific and can be measured [11]. Carneiro et al. [12] stated that these stress responses can be divided into the following four main categories:

1) physiological,
2) physical,
3) behavioral, and
4) performance.

Furthermore, Alberdi et al. [13] stated that humans show psychological responses to the stress as well. Fig. 1 shows this

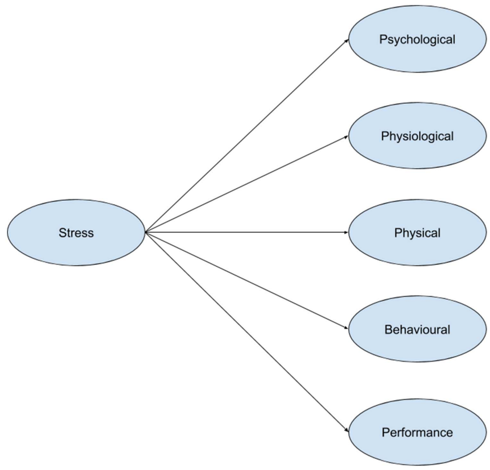


Fig. 1. Multimodel nature of stress responses.

multimodel nature of human body's response to stress. Observing and identifying changes in these responses enable detecting stress level changes of a person via different techniques.

Commonly used methods to identify psychological stress responses are using self-reported questionnaires and being interviewed by a psychologist [13]. Self-reported questionnaires are considered as the most reliable approach of this. Some of the popular self-reported questionnaires used are Stress Self Rating Scale (SSRS) [14], Perceived Stress Scale (PSS) [15], and Stress Response Inventory (SRI) [16], [17].

In contrast, physiological responses mainly occur due to stress-related responses of autonomic nervous system (ANS) and cannot be observed with the naked eye [12], [13]. These responses affect physiological signals, such as galvanic skin response (GSR), heart rate variability (HRV), brain waves, blood pressure (BP), as well as hormone levels. Measuring these signals requires various types of special equipment, such as functional magnetic resonance imaging (fMRI) and electrocardiogram (ECG), and usually performed in a laboratory environment.

However, physical and behavioral responses are visible to the outside world and can be identified by careful observation of a person. Therefore, these observations can be done in a home environment as well as in a laboratory environment with equipment that are commonly available. Furthermore, these observations can be made while a person perform their usual day-to-day activities, such as driving, browsing the Internet, or playing a video game.

As detailed earlier, gameplay is an activity that people undertake frequently and spend a significant time on, especially during the recent pandemic. If such an activity that people undertake frequently and voluntarily can be utilized to detect and monitor their stress and flag that any precautionary actions can be taken well in advance preventing any serious adverse long-term effects on health. With that goal, this survey reviews the literature in order to answer the research question: "What types of existing stress-detection techniques can we leverage to automatically detect stress during gameplay?"

The rest of this article is organized as follows. First, we discuss the methodology followed in the literature survey. Next, we investigate the methods that need to be performed in a laboratory environment due to the requirement of special equipment for stress detection. Thereafter, we investigate the stress-detection methods that can be used in a home setting. Finally, we discuss which of these methods can be incorporated with gameplay for stress detection in day-to-day life.

## II. Survey Methodology

In order to understand the strengths and weaknesses of different stress-detection methods, we first focused on identifying the state-of-the-art stress-detection methods without limiting to the methods that can only be applied within games. Therefore, we first reviewed the papers that discuss about stress detection in general, such as [13]. To search for such literature, we undertook the search using the keywords including, but not limited to, stress or mental health and detection or monitoring or recognition. At this initial stage, we only considered the literature published after 2015 since we expected that recently published literature on aforementioned topics would discuss stress-detection methods experimented in past as well as in recent times. Furthermore, since we used Google scholar for these steps, any publication that was not peer reviewed was not considered for the review. Once the literature was identified, abstracts of the papers were reviewed first to see if each paper was relevant to our research and irrelevant papers were also omitted. Furthermore, we did not review papers that focused on one particular stress-detection methodology at this stage, as the goal of this step was to identify different stress-detection methods. However, such papers were noted to be used in the next step where we reviewed each stress-detection technique in detail. From the literature reviewed at this stage, we identified a list of stress-detection techniques (types of sensors, methodologies used, etc.) that can be used during gameplay in order to answer the research question: "What types of existing stress-detection techniques can we leverage to automatically detect stress during gameplay?" This led to the compilation of a comprehensive list of approaches that can be used for the stress detection during gameplay. However, it is expected that these techniques will require modifications in order to adapt to the gameplay environments.

Thereafter, we searched for research that explored each identified stress-detection method. To achieve this, we started to search literature using backward snowballing [18] starting from the initial set of papers where we identified relevant research by looking into the references of the papers. After this first iteration, we identified an initial set of papers to review each stress-detection technique we identified. In addition, we also performed one iteration of forward snowballing on the papers identified in this step to identify more recent research for each stress-detection technique. In this step, we used Google Scholar to searching for papers as it provided easier and efficient means to traverse through citations of papers. For techniques where snowballing did not lead us to sufficient papers (e.g., game controller-based approach), we further searched for literature using keywords in Google Scholar as well as in other libraries, such as IEEE digital library.

The identified research for each stress-detection approach was then reviewed to identify information on following aspects of the approach:

1) general methodology followed when using the approach for stress detection,
2) particular equipment required/used,
3) algorithms used for data analysis and stress detection,
4) obtained level of accuracy,
5) advantages and disadvantages.

If the snowballing approach did not reveal sufficient details for a particular methodology, we also used keyword searching in search for further details. Whether we went to keyword-based search or not was not based on the number of articles, but on the amount of details we discovered at the previous step. For example, if we could not find data analysis techniques used with computer keyboard-based stress detection, we used search terms such as "stress-detection keyboard."

Once the relevant literature is identified and shortlisted, we used Nvivo [19] for taking notes during the review process. Nvivo provides an easier way to extract useful information from papers relevant to different stress-detection approaches and aforementioned information categories. Papers were reviewed by the first author, and while reviewing the papers, texts relevant to aforementioned information types were extracted and mapped to the information category (example categories: equipment used for fMRI, advantages of fMRI, disadvantages of fMRI, etc.).

In cases where the reviewer identified any new stress-detection approaches that were not identified initially, they were also noted and reviewed to include in the final results.

## III. Summary of Results

A total of 112 research papers were reviewed in this review and 22 different techniques for detecting stress were identified. Next three sections investigate the different stress-detection techniques that were identified. We have divided the identified methods into two sections, such as techniques suitable for laboratory settings and techniques suitable for home settings considering the costs of the sensors, physical size, and ease of use. This categorization was undertaken for the ease of presentation considering criteria, such as intrusiveness (i.e., need to have skin contact) and cost. This should not be viewed as a strict categorization. It is possible some of these techniques can be used in both environments due to the fact that some of the technologies are becoming cheaper day by day.

## IV. Stress-Detection Techniques for Laboratory Settings

### A. Invasive Methods

Unusual amounts of hormones in blood is a common symptom associated with stress. When an individual is experiencing a stress condition, the amount of stress hormones (e.g., cortisol or catecholamine levels) that are released gets increased. These variations of the hormone release can be measured via invasive methods, such as taking urine, saliva, or blood samples [20], [21], [22], [23], [24], [25]. For example, Netterstrøm et al. [26] reported that measuring the amount of glycated hemoglobin in blood would indicate the stress level. However, these type of stress measurement techniques require lengthy and complex analysis procedures conducted by professionals [25].

### B. Blood Pressure (BP)

BP is the pressure applied on the walls of blood vessels when circulating blood. It can fluctuate between a systolic (maximum) and a diastolic (minimum) pressure [25]. Some of the commonly used tools to measure BP are Finapres (FINger Arterial PRESsure) monitor system, Ambulatory Blood Pressure Monitor (ABPM-50) [25], or a combination of a stethoscope and a sphyngomanometer [27]. Studies have found an increase in BP in response to the increase of stress [28], [29]. However, Hjortskov et al. [30] discovered an increased BP both in stressful situations as well as in controlled situations, without indicating any substantial difference. Furthermore, measuring BP is intrusive and disruptive as it requires wrapping of a cuff around an arm or finger.

### C. Blood Volume Pulse (BVP)

Blood volume refers to the total amount of blood in a blood tissue during a given time period [25]. BVP is a measure of the amount of light reflected by the surface of the skin. Changes in light reflections are affected by blood circulation and, therefore, provides measurements for changes of blood vessels and heart rate. BVP has been identified to be negatively correlated with the stress that a person is experiencing [31].

A popular measurement of BVP uses photoplethysmography (PPG) where a PPG reflects infrared light on the skin and the amount of light bounced is measured as a measurement of the amount of blood available in the area [25], [32]. Zhai et al. [33] used BVP along with other techniques to detect stress of computer users. They measured BVP from sensors placed on users' hand and modeled stress with a support vector machine (SVM)-based classifier that used BVP along with other measurements. Mcduff et al. [34] reported a study that used a camera to record facial regions of participants and estimated BVP using a PPG signal processed with independent component analysis. They used the estimated BVP to derive heart rate, HRV, and respiration rate details of the ten participants. These derived values were used to predict stress levels of participants, which resulted in a 85% accuracy.

Chigira et al. [32] presented a computer mouse with a PPG surface that can detect BVP of computer users. Their results indicated the applicability of the developed mouse to calculate the HRV of people by measuring their BVP. According to the details presented in these studies, it can be noted that BVP is a measurement of stress that can be measured less intrusively compared with other physiological measurements of stress. Instruments, such as the computer mouse proposed by Chigira et al. [32], would enable this measurement to be used in home environments to measure stress conditions of people.

### *D. Electrocardiogram (ECG)*

ECG is "the recording on the body surface of the electrical activity generated by heart" [13], [35]. It is a very commonly used measurement in stress research as it directly reflects on heart activity and highly sensitive to heart rate and HRV. Measurements are usually recorded by putting some electrodes on identified places of the body and measuring the potential voltage difference [13]. The most useful features derived from ECG data are probably related to HRV.

Wijsman et al. [36] measured ECG along with respiration, skin conductance, and electromyogram (EMG) of the trapezius muscles of 30 participants using a wireless body sensor network. They extracted five features from ECG data, which are heart rate, standard deviation of interbeat intervals, low-frequency (LF) HRV, high-frequency (HF) HRV, and LF/HF ratio of HRV. Their final classification model used five features including only one feature extracted from ECG data, which is heart rate. It correctly classified 80% of data related to the nonstressed condition and 69.1% of data corresponding to the stressed condition.

In a study reported by Palanisamy et al. [37], they attempted to identify stress using different types of physiological signals including ECG and HRV. Their evaluation was conducted with 40 participants. For collecting ECG data, three ECG electrodes [silver (Ag)/silver chloride (AgCl)] were positioned following Einthoven triangle placement. Collected ECG data were used to extract six ECG features and five HRV features. Classification models were created using k nearest neighbor (k-NN) and probabilistic neural network (PNN) classifiers for ECG and HRV features separately, where HRV classifier achieved 93.75% accuracy and ECG classifier achieved 76.25% accuracy for stress detection.

Hjortskov et al. [30] also used ECG recordings in a study they conducted to assess stress levels of computer users. They calculated HRV from ECG data and observed a decrease in the HF component of HRV and a rise in the LF/HF ratio in the stress situation compared with the controlled scenario. They remarked HRV as a "more sensitive and selective measure" of mental stress. Vendeput et al. [38] also used ECG signals to detect mental and physical stress of people by measuring HRV. ECG was measured by placing electrodes (Ag-AgCl, 10 mm diameter) on the body. They pointed out that mental stress reduced HF components of the HRV interval, while increasing LF ones. Vendeput et al. [38] also remarked HRV measured with ECG as a very useful and inexpensive tool to detect mental and physical stress.

Cinaz et al. [39] used data collected with ECG to classify office workers' mental workload into three categories: low, medium, and high. ECG data of experiment participants were collected using a Zephyr BioHarness chest belt and used to extract HRV features of participants. Based on the collected results, they classified the HRV features into two groups where some features increased and some features decreased with the raise of mental workload.

In addition to this research, ECG can be identified as one of the vastly employed measurements in stress measurement systems that use features from multiple data collection methods. In a review conducted by Alberdi et al. [13], they observed that ECG has been used in vast majority of studies that achieved high accuracy rates.

### *E. Electroencephalography (EEG)*

EEG is used to measure the electrical activity of the brain. It uses a collection of discs (electrodes) positioned on the person's scalp to observe brain's electrical activities [13]. It is a widely used technique to record stress-related brain activity variation because of the high temporal resolution, relatively low intrusive equipment, and cost effectiveness [25] compared with other methods available for monitoring brain activities (e.g., fMRI).

Seo et al. [17] investigated the relationship between EEG, ECG, and stress hormone levels for assessing chronic stress, using the Self-Assessment Manikin test and the SRI as ground truth. The EEG was monitored with Ag-AgCl electrodes positioned on four nomenclature (MCN) system sites: FC5, FC6, O1, and O2. A substantial positive correlation was identified between the cortisol hormone levels and the high beta activity at the anterior temporal sites, remarking the correlation between the beta band and stress. It was found that the mean high beta power at the anterior temporal sites of the stress group was identified to be substantially higher compared with the control group.

Lim and Chia [40] reported an experiment where they used EEG signals for detecting cognitive stress levels of 25 participants. They recorded EEG data of their participants using the NeuroSky's single-electrode MindWave EEG headset while participants are performing a Stroop Color-Word Interference Test. A kNN-based classification model that used the collected EEG data achieved 72% accuracy when used to predict stress levels of participants.

Das et al. [41] presented an approach to classify stress conditions using EEG, GSR, and PPG data. EEG of 22 participants was monitored using the four-channel Muse4 2016 headband. When analyzing the collected data, they obtained time series of power contained in $\alpha, \beta, \gamma, \delta$, and $\Theta$ bands and statistical parameters, such as median, standard deviation, skewness, kurtosis, minimum, and maximum, were extracted. Furthermore, three additional Hjorth parameters were also determined. The classification model developed using the top ten features obtained a median accuracy of 68.2%.

A neurofeedback video game called MindLight uses EEG to detect player anxiety symptoms to train the players to relax as a treatment [42]. In this game, EEG signals are obtained through a one-channel, dry sensor EEG headset. These inputs are used to detect the player's anxiety symptoms, where changes in brain signals, such as decrease in relative beta power and increase in relative alpha power, have been identified as indications of anxiety and calmness. Difficulty of the game is adapted based on the anxiety, practicing players to keep their anxiety at a minimum level to progress with the game.

Zhang et al. [43] reported a study where they attempted to predict mental workload of 16 people with EEG, ECG, and GSR data. A full-head EEG cap of 40-channels was used to collect EEG data of the participants. They used a technique called "a filter bank common spatial pattern filtering technique" to extract neural activity pattern details from the collected EEG data. The classification model that used these EEG data achieved an accuracy of 87.5%, which was better than classification models that were created with ECG and GSR data.

While EEG can be used in a relatively less intrusive manner compared with other techniques and is reliable, still cost of EEG equipment is relatively expensive.

### F. Galvanic Skin Response (GSR)

GSR is a measure of the electrical conductance of the skin. When a person is experiencing stress, skin conductance is raised due to the higher humidity level on the skin surface, which raises the flow of electricity [25], [44]. This can be computed by positioning two electrodes on the skin surface in a close proximity and applying a weak electrical current between them.

Healey et al. [45] reported a study where they measured various physiological signals, including GSR of 24 drivers while they were driving. GSR was measured in two positions: on the palm of the left hand and on the sole of the left foot. Their results indicated that GSR and HRV measurements are the best cues for real-time stress-level monitoring out of the used measurements.

The study by Zhai et al. [33] used GSR along with several other methods for detecting stress of computer users. They extracted five features from the GSR data that were collected from two users, which were number of responses, mean value of GSR, amplitude of the response, rising time of the response, and energy of the response. They combined GSR features with collected other measurements to build a classifier that detected stressed and relaxed conditions (accuracy = 90.1%).

In a study performed by Sinha et al. [46] to analyze the stress dynamics of an examinee during a multiple-choice question (MCQ) test, they used GSR as an estimation of stress. GSR data were collected by applying a constant voltage to the skin through two electrodes. Stress measurement was performed using a score calculated by analyzing the fluctuation of the GSR signal. Results showed a substantial correlation between the difficulty of the MCQs and the GSR signals.

De Santos Sierra et al. [47] created individual stress templates for 80 individuals using GSR and HR signals and a fuzzy logic algorithm. The model that used a combination of features extracted from both these inputs resulted in a classification accuracy of 99.5%.

In the study performed by Palanisamy et al. [37], they evaluated the use of GSR for stress detection (Section IV-D already discussed their results related to HRV measurements). They acquired GSR data by a GSR electrode positioned on the user's hand between two fingers. They extracted nine features from GSR data and developed k-NN and PNN classifiers using those features. PNN classifier achieved the best accuracy of 70.83% for GSR data; however, it was the lowest performance compared with the other five different types of psychological inputs.

Section IV-E already reviewed the EEG results revealed by Das et al. [41], where they used EEG, GSR and PPG data for stress classification. In their study, they gathered GSR data using a single Shimmer 3 GSR+2 unit that used gel-based electrodes. These electrodes were placed between the middle and proximal digital creases of the second and third digits of the nondominant hand. They extracted a number of features under stressful and nonstressful conditions, including rise time, area under the curve corresponding to the rising part, half-recovery time, the kurtosis of the orienting response, detrended fluctuation analysis slope, mean power during task, and the ratio of fluctuation index during stress and relax. Classification model developed using the random forest (RF) algorithm achieved a median classification accuracy of 72.7%.

In a study performed by Hernandez et al. [48] to detect variations of keyboard and mouse activities under stress, they used GSR as an approximation for stress level. For this purpose, GSR data were collected using the QTM sensor. Their findings indicated an overall pattern of increased GSR readings under stressed conditions.

While GSR data when combined with other measurements give high accuracy results (and even can be relatively cheaper), this technique requires skin contact.

### G. Electromyogram (EMG)

An EMG assesses the electrical activity of muscles with the use of electrodes. Stress has been identified as a factor that elevates the muscle tone [13], and therefore, various researchers have attempted to use EMG to detect stress of people.

The study by Palanisamy et al. [37] used EMG along with other psychological measurements for stress detection. EMG signals were acquired by placing bipolar (Ag/AgCl) gold plated reusable electrodes on the left Trapezius muscle. In total, six features were identified from the collected EMG signals and employed to develop classifiers with kNN and PNN algorithms. EMG-based classifier showed a classification accuracy of 71.25%.

In the research performed by Wijsman et al. [36], they measured EMG of the trapezius muscle with several other measurement using a wireless body sensor network. Bipolar EMG signals were recorded from the upper trapezius muscles of both shoulders by placing two electrodes. They extracted eight features from the EMG signals collected from 30 participants, which are root mean square of the EMG signal, static load, median load, peak load, gaps per minute, relative time with gaps, mean EMG frequency, and median EMG frequency. Their final classification model used five features from collected multiple inputs including one feature from EMG data, which is gaps per minute. It correctly classified 80% of data related to the nonstressed condition and 69.1% of data corresponding to the stressed condition.

Wei et al. [49] reported a study they conducted to detect stress conditions using EMG and respiration signals. After features are extracted from the collected data, they used Fisher linear discriminant classifier to detect stress levels. Their classifier indicated a classification accuracy of 97.8% and authors remarked that EMG signals performed better compared with respiration data when used to detect stress levels.

Sharma and Gedeon [25] remarked that the performance of EMG-based stress detectors is lower when compared with detectors that use other measurements, such as GSR and HRV. Furthermore, Alberdi et al. [13] highlighted that similar to other physiological measurements, obtaining EMG data from people can be obtrusive. Similar to the GSR method, EMG-based methods requires subjects to wear the EMG sensors.

### H. Functional Magnetic Resonance Imaging (fMRI)

fMRI is a method that can be used to monitor brain activities by detecting changes in oxygen saturation and the flow of blood [13]. Some of the main advantages of using fMRI is its noninvasiveness and not using radiation. While it has a good spatial resolution, it does not result in a good temporal resolution [13].

Hayashi et al. [14] reported a study they conducted to investigate whether stress conditions has any effect on brain responses in the areas related to emotional and cognitive processing. Structural and functional imaging data were acquired using a 3T whole body scanner. Their results indicated that the brain regions involved in cognitive processing showed reduced activity in high-stress holders compared with low-stress holders. However, this method is intrusive.

### I. Respiration

Researchers have observed that respiration patterns change when the stress conditions change [13], [49]. A couple of studies that are already presented in this review used respiration along with other physiological measurements for identifying stress levels [45], [49]. In both these cases, performance of respiration data was lower compared with other signals. Furthermore, collecting respiration data usually requires subjects to wear a belt around their body, which is intrusive and may prevent them from carrying out their usual activities.

### J. Skin Temperature

Researchers have identified that stress levels are correlated with the skin temperature [31]. Skin temperature can be conveniently measured by positioning a thermal sensor on the skin.

Kataoka et al. [50] reported a study they performed to investigate the relationship between the stress level and the skin temperature. Their results indicated a relationship between stress and skin temperatures on nose and forehead. Thereafter, they developed a system that consists of an infra-red camera and a color camera that can measure the skin temperature without a skin contact.

However, not all of researchers agree on the effect that stress has on skin temperature. While some researchers found the skin temperature to increase when under stress [28], [37], while some researchers found the opposite of this [51], [52].

### K. Thermal Imaging

Researchers have conducted studies that indicated the applicability of thermal imaging for stress detection by identifying temperature changes that are caused by stress. Levine et al. [53] reported the development of a high-resolution thermal imaging system to measure stress. They analyzed the temperature variation of the corrugator muscle placed above the eye area and concluded that considerable and consistent increase of temperature in corrugator muscle was occurred with all the subjects while they are experiencing stress. They highlighted the ability to identify these changes with thermal imaging due to the lack of adipose tissue above the corrugator muscle, which minimizes the thermal energy required for simulating changes on the surface.

Mohd et al. [54] investigated on vision-based systems for physiological measurements as those do not require any contact with the user. They identified that the amount of blood flown in three facial areas, which are periorbital, supraorbital, and maxillary, is related to the stress level that the person is experiencing. They proposed to measure the heat dissipated by this increased blood flow using thermal imaging.

Sharma et al. [55] reported a research they conducted to study the applicability of thermal imaging and visual imaging for stress detection. They used an FLIR infrared camera for capturing thermal videos of 35 participants. SVM-based classifier that used features from both visual and thermal imaging achieved an accuracy of 86% for stress detection.

Thermal imaging can be obtained nonintrusively; however, accuracy of the images can be affected by other environmental factors that are difficult to control in a home environment.

## V. Stress-Detection Techniques for a Home Setting

### A. Voice and Speech

Human voice has been found to show observable changes in some characteristics in response to stressors [56]. Especially, high stress levels result in the rise of range and quick variations in fundamental frequency [57], [58], [59] and increase in energy for high-frequency voice components [60].

Lu et al. [61] investigated the ability to detect stress from a voice-based stress recognition system attached to smart phones. They used Nexus One phones for collecting data from 14 users. Main features that were extracted are standard deviation of pitch, pitch range, pitch jitter, centroid frequency of the spectrum, ratio of energy above 500 Hz, rate of speech, cepstral representation of the voice, and Teager Energy Operator-based nonlinear transformation. The classification model that used Gaussian mixture models with diagonal covariance matrix achieved 81% and 76% of accuracies for stress detection in indoor environments and outdoor environments, respectively.

Demanko and Jastrzebska [62] presented an analysis they performed on 107 police call center recordings in order to identify stressed and normal conditions. For stress detection, nine features were extracted from call recordings, which are average, highest and lowest fundamental frequencies, fundamental frequency variation, jitter, amplitude perturbation quotient, degree of sub harmonic segments, noise-to-harmonic ratio, and degree of voiceless. Their linear discriminant analysis-based classifier obtained 80% accuracy for classifying male stressed and neutral, female stressed, and neutral speech classes.

Kurniwan et al. [63] reported a study they performed to develop stress-detection models using GSR and speech data. From speech data collected with ten participants, they extracted the overlapping time frames, voiced and unvoiced speech, pitch, Mel Frequency Cepstral Coefficients (MFCCs) that represent human audio perception, and Relative Spectral Transform-Perceptual Linear Perception (RASTA-PLP) features. MFCC features appeared to be the best indicators of the stress where SVM-based detector that used those features achieved a 92.6% accuracy for detecting light and heavy workload scenarios.

Measuring stress using speech is noninvasive, less obtrusive, and less costly compared with other approaches for detecting stress [25]. One of the main limitations for using voice and speech for stress recognition is that precise speech analysis requires the sound quality to be high, which is not always the case in real-world scenarios. Therefore, stress detection using voice can be less useful both in quiet and noisy environments [13].

### B. Pupil Dilation (PD)

Researchers have used PD as a measurement for stress detection. The pupil dilates at a higher rate when an individual's pupil diameter increases indicating that a person is perhaps experiencing a higher level of stress. [25].

Barreto et al. [64] used pupil diameter along with several other measurements in a stress-detection system that they developed. They used ASL-504 eye-gaze tracking system to record PD data of 32 participants and used the collected data to extract the mean value of PD. They developed classifiers with Naive Bayes, decision tree, and SVM algorithms using combinations of various collected inputs. They observed a considerable reduction of accuracy when PD inputs are removed from the classifier, which highlighted the PD as a good indicator of stress (accuracy with PD: 90% and accuracy without PD: 61.5%). A similar study conducted by Zhai and Barrato [33] also indicated PD as the best measurement of stress among BVP, HRV, skin temperature, and PD data.

In a study performed by Liao et al. [44], they collected video recordings of participants and extracted the percentage of large PD and pupil ratio variation features from the collected data. They observed that participants' pupils dilated more often when they are under stress. They observed a positive correlation between stress and percentage of large PD.

Sakomoto et al. [65] reported a study they performed to identify the relationship of pupil diameter and workload stress of participants. They monitored and recorded the pupil diameter of participants using an infrared video camera while participants were following some tasks. They observed a substantial relationship between the frequency feature of pupil diameter variability and mental state, and therefore, concluded that the frequency of pupil diameter variability is perhaps a helpful measurement for measuring stress.

Ren et al. [66] also reported a study where they used PD and GSR data to detect stress of people. They recorded the PD data of participants using a TOBII T60 system while participants are performing the Stroop color–word interference test. Thereafter, they extracted "average value of the PD signal in a segment," "maximum value of the PD signal in a segment," and "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" using the collected PD data. They observed the best accuracy for stress detection when PD data are used without GSR data for all five different classification algorithms they used.

PD is a reliable method that can be used less intrusively when people play games.

### C. Eye Gaze

Eye gaze indicates where an individual's attention is focused on. It provides an approach to identifying the individual's emotional states and objectives [25]. Eye gaze records can be easily obtained at home using a web cam. Research that used this method has used off the shelf web cams [67] as well as special eye trackers, such as Tobii EyeX controller [68], [69]. Eye pupils' positions have been recorded for eye gaze tracking, as well as for extracting the Gaze Spatial Distribution (GazeDis) and saccadic eye movement percentage (PerSac) [44].

In the research presented by Liao et al. [44], they used eye gaze data along with several other measurements to perform real-time stress monitoring. Eye gaze data were identified from video recordings that were collected in the study. The eye detection and tracking approach that they followed used the appearance-based mean-shift tracking technique and the bright pupil effect under Infrared light sources. They observed that as stress increases, participants focused the eye gaze on the screen. Furthermore, most of the times, the correlation between stress and GazeDis was positive.

Wang et al. [68] proposed a noninvasive approach for stress detection based on users' eye gaze and gaze-mouse coordination patterns. They collected users' eye gaze and mouse control data while performing a task under stress and under normal conditions. They used Tobii EyeX controller that records $x$- and $y$-coordinates of nine subjects' gaze for collecting eye gaze data. Based on the collected data, they extracted features related to eye gaze movement and gaze mouse coordination and created a classification model based on the RF algorithm. Their model achieved a correctly classified rate of 94.4% when both types of features are used for the classification for nine subjects. Their finding also indicated that when a user is stressed, they are more motivated to stay on the task, and therefore, gaze patterns are more consistent.

In a study performed by Huang et al. [67] to investigate the impact of mental stress on gaze click patterns, they used an off the shelf web cam to record visuals of users' heads and shoulders while users are performing a task under different stress conditions. They extracted eight features related to gaze click patterns, such as "existence of a fixation in the 0.5 s period preceding a click" and "duration of the fixation corresponding to a click." They observed that gaze usually shifted away from the fixation point before the click event under stressed conditions. Furthermore, two gaze-click features, "the closest fixation duration preceding/during a click" and "the reaction latency after a click," showed a fair amount of negative correlation with stress. In addition, they discovered that user-dependent models based on these features give better correct classification rates compared with user-independent classification models created with these features.

One of the main limitations of the aforementioned two works by Wang et al. [68] and Huang et al. [67] is that feature extraction required prior awareness of the user interface (UI) layout. To address these issues, Wang et al. [69] introduced a stress-detection system that can identify user stress conditions without being worried about the UI specifics. Their model mainly used relative movement features of the mouse and gaze, and used decision tree and RF algorithms for the classification. Testing of the system with 15 users revealed that it is capable of correctly predicting user stress levels with 74.3% accuracy level for dynamic UIs and 76.6% accuracy for fixed UIs. In addition to the aforementioned observations of these three studies, it should be noticed that the mental math calculation task used in these experiments have many features that are common in computer games.

Similar to PD, eye gaze is a reliable method that can be used less intrusively when people play games.

### D. Blink Rates

Researchers have observed conflicting outcomes on the interconnection between stress and blink rate. Haak et al. [70] presented the findings of a study they conducted to detect stress using eye blink data. They recorded user EEG data using the TruScan 32 EEG system with 19 electrodes placed according to the 10–20 placement standards and used the collected EEG data to calculate blink rates. Their results indicated that eye blink frequency increases in stressful situations. Mohd et al. [54] also measured blink rates of experiment participants where they used a visible stereo camera to capture the blink rates. They also concluded that blink rate has a substantial relationship with mental stress.

However, in the previously reviewed study by Liao et al. [44], their observations indicated that blink rate reduces when the user is stressed. Therefore, this method requires further investigation.

### E. Facial Expressions

Researchers have identified facial expressions as a parameter that can be used to detect stress of people [13], [25], [71]. Stress conditions have been identified by employing manual observation of facial expressions as well as by using automated methods [72], [73]. The main advantage of using facial expressions for stress detection is its unobtrusive nature compared with other stress measurements.

Dinges et al. [74] presented a study they conducted to identify the stress of spacecraft pilots by detecting their facial expressions. The hidden Markov model-based classifier that used facial expressions of 60 participants for stress detection obtained a classification accuracy of 68%.

Giannakakis et al. [75] reported a method for stress/anxiety emotional state detection, which used video-recorded facial signals. Their investigation considered features, including eye, mouth, and head motion activities as well as heart rate measurements, obtained using camera-based PPG. They concluded that specific facial signals, obtained from eye, mouth, head movements, and heart activities, result in a high accuracy and are useful as distinctive measures of stress and anxiety.

Aigrain et al. [76] reported a study where they used behavioral and facial expressions to detect stress. They recorded the face of 14 participants with a high-definition camera and extracted 12 features of facial expressions related to activation levels of 12 action units, which are inner brow raise, outer brow raiser, brow lower, upper lid raiser, cheek raiser, nose wrinkler, lip corner puller, lip corner depressor, chin raiser, lip stretcher, lips part, and jaw drop. Their classification model that used SVM classifier with facial features achieved 68% accuracy, which was lower compared with the accuracy of the classifier that used body movement features.

Das and Yamada [77] developed a framework to mathematically model the instant stress of an individual using images that capture facial expressions. To analyze facial image data, they identified features related to facial action units. Their research resulted in an equation for measuring the stress numerically from facial expressions.

In the previously presented work by Liao et al. [44], they captured facial videos of participants and extracted facial expression features, which are average eye closure speed and mouth openness. They claimed that participants move the head and open the mouth less frequently as stress decreases.

Bevilacqua et al. [78] developed a facial expression-based method to distinguish stress and boredom during computer gameplay. Facial recordings of 20 participants were collected during a gameplay session using Canon Legria HF R606 video camera and were used for feature extraction. Seven facial features, such as mouth outer zygomatic muscle activity, mouth corner zygomatic muscle activity, eye area orbicularis oculi muscle activity, eyebrow activity, facial movement to and away from camera, total head movement in any direction in a short duration, and overall movement of all 68 facial landmarks were extracted from the collected data along with heart rate estimated using the remote photoplethysmography technique. The neural network-based classifier developed with only facial features achieved a classification accuracy of 59.4%. This was slightly increased when additional heart rate data were also provided for the classifier. Facial expressions-based stress detection is a method that can be used when people play games.

### F. Gesture and Movement

Various researchers have highlighted body language and body movements as indications of stress that an individual is experiencing. In the previously explained study by Aigrain et al. [76], they used such behavioral data along with facial expression data for stress detection. They collected body movement data by video recording whole body and the skeleton using Kinect. From the collected data, they extracted 16 features related to three categories, which are "the Quantity of Movement and its derivatives," "the detection of periods of high activity and posture changes," and "the detection of self-touching in the region of the head." The SVM-based classifier that used these features achieved an accuracy of 80%.

Arnrich et al. [79] presented a study where they attempted to detect stress of 33 office workers by observing their posture. They used the CONFORMat system [80], developed by Tekscan to record the variation of force on the chair that is put by the participants. They extract posture-related features from collected data, such as the center of pressure. Using spectral information, accuracy of 73.75% was obtained when detecting stress situations, indicating that the postural behavior information are correlated with the stress levels.

Body posture-related data are also a type of data that can be used in a computer gameplay environment; however, especially designed equipment (such as the CONFORMat system [80]) may be needed.

### G. Keyboard Data

Keystroke dynamics investigate the distinctive timing patterns in typing, and usually uses keystroke timing features (e.g., the duration of a key press and the time interval between key presses [81]). Initially, keystroke dynamics were used as an authentication mechanism [82], [83], [84], [85], and thereafter, various researchers have considered keystroke dynamics for detecting stress as well as various other emotional states of computer users. These measurements can be obtained from the way that a person uses a keyboard to do their usual computer activities. In addition, some researchers have investigated the change of pressure of key press events under different stress conditions.

Vizer et al. [86] reported an investigation of detecting mental and physical stress using keystroke and linguistic features. In total, 24 participants created free text and fixed text samples using a keyboard under baseline, control, physically stressed, and mentally stressed conditions. The data collection was performed for each keystroke, and collected data consisted of the event type (e.g., key up or key down), time stamp, and the key identifier. Main keystroke features used for analysis are timing features (time per keystroke, pause length, and pause rate) and frequency of particular special characters (e.g., backspace, delete, return, etc.). They were used in both raw and normalized forms for creating classification models using decision tree, SVM, kNN, AdaBoost, and artificial neural network (ANN) algorithms. Results indicated that mental and physical stress can introduce changes into typing patterns that can be detected by employing machine learning algorithms. Feature sets that showed significant differences when compared between control and stressed conditions varied for raw data and normalized data as well as for physical and cognitive stress. While all machine learning algorithms resulted in accuracy rates better than chance, classification accuracy of the used machine learning techniques varied based on the aforementioned conditions. They achieved 75% accuracy for cognitive stress when kNN algorithm was applied for normalized data and achieved 62.5% accuracy for physical stress (AdaBoost with raw data, SVM, and ANN with normalized data).

Rodrigues et al. [87] presented a study they conducted to investigate the possibility of identifying e-learning users' stress using the study of mouse and keyboard consumption. In the experiment, they recorded the keystroke rate and the average duration of a keystroke along with mouse click dynamics and user task performance data under different stress conditions. Their results indicated that when stressed, rate of keyboard pressing is considerably higher than that of a relaxed student. Furthermore, it was reported that when stressed the keyboard pressing is more intense and the backspace key is more frequently used. Based on the results obtained by Rodrigues et al. [87], Gomes et al. [88] used time between keys and key down time along with several mouse dynamic parameters as indications of users' stress for creating a stress recognition module.

Hernandez et al. [48] used a pressure sensitive keyboard to identify the relationship between keyboard dynamics and the cognitive state of the user. They used a keyboard that provides measurements ranging from 0 to 254 based on the pressure applied when pressing a key. The results showed that 79% of the participants significantly increased the typing pressure under stress.

Epp et al. [81] conducted an experiment where they attempted to identify 15 different emotions of computer users based on their typing patterns on a normal keyboard. They collected keyboard dynamic inputs of computer users while they are performing their day to day computers tasks. They used a C#-based data collection program and an operating system level tool to record each keystroke. The collected unprocessed keyboard data included key press and release events, unique identifiers for each key, and a timestamp for each event. They used the collected data to generate keystroke duration and keystroke latency related features for single keystrokes as well as for digraphs (pairs of consecutive key strokes) and trigraphs (three consecutive key strokes). They used 13 aggregate features for generating the classification models that were produced using the C4.5 machine learning technique. They claimed that they achieved best accuracy values for classifying confidence, hesitance, nervousness, relaxation, sadness, and tired emotions. They do not mention stress as an emotion that could be predicted with a higher accuracy.

Alhothali [89] explained a system for classifying emotions in an intelligent tutoring system. While users interact with the system, their keystrokes data were gathered and used to extract 18 features of three types [i.e., timing features (e.g., pause rate), typing features (e.g., typing speed), and response features (e.g., response quality)]. Classifiers based on discriminant analysis (linear and quadratic), naive Bayes, kNN, decision trees, and ANN were modeled to classify collected data into positive and negative valance as well as for three emotional states (confusion, boredom, and frustration). Alhothali [89] remarked that typing speed, key latency, and key duration feature only have a weak correlation with mental changes.

Khanna and Sasikumar [90] recorded keystrokes data of 41 participants under different emotional states to identify relationships between emotions and keystroke patterns. The features they extracted are typing speed, mode, standard deviation, standard variance and range of number of characters typed in 5-intervals, total time taken for typing, total number of backspace usages, and the period where the user is doing any tasks with the keyboard. They applied linear logistic regression, SVM, neural networks, random tree, C4.5 tree, and binary tree classification methods to identify positive, negative, and neutral emotions based on those features.

Lv et al. [91] used data collected through a pressure-sensitive keyboard as an attempt to recognize different mental states (anger, fear, happiness, sadness, surprise, and neutral) of computer users. In addition to typical time-related features of keystrokes, this experiment collected pressure applied on keys for keystrokes. kNN classifier was used to recognize aforementioned six emotions based on these data.

There are several advantages and disadvantages of using keystroke data for stress and emotion detection. Since no special hardware is required, keystroke data can be considered as a natural type of biometrics . Moreover, they are less intrusive compared with most of the other stress-detection techniques [13], [86], [92]. Data collection can be performed while the user is performing their day-to-day computer activities [92] and also can be collected continuously for a lengthy time period [86]. Furthermore, Vizer et al. [86] stated that using the keystroke data to detect stress are less computationally intensive compared with other techniques. However, the major limitation of this technique is that keystroke patterns tend to vary on conditions other than stress as well, such as type of software and hardware used, time they were recorded, and the person being recorded.

### *H. Mouse Data*

Commonly used features that are related to mouse dynamics are mouse speed (both horizontal and vertical), acceleration, movement frequency, stillness, mouse coordinates, total distance, and the direction. The ratio of average speed and the distance traveled as well as the ratio of average speed and the movement direction have been also used by researchers for stress-detection purposes [13]. Another popular set of features commonly used are the number of mouse clicks, absolute sum of angles, and movement of the wheel [13], [48], [93], [94]. These measurements can be obtained from the way that a person uses a mouse to do their usual computer activities. Various researchers have evaluated the applicability of mouse dynamics in identifying stress and emotional states of computer users.

In the study that Rodrigues et al. [87] performed to detect stress of e-learning students, they used mouse dynamics data along with keyboard data. They extracted click accuracy, click duration, amount of mouse movement, amount of mouse clicks, and its frequency details from the collected mouse movement data. They identified that stressed students more frequently used the mouse compared with relaxed students.

Liao et al. [44] presented a real-time stress-detection system where they used physiological data and behavioral data collected through an emotional mouse along with physical appearance evidence, such as facial expression, eye movements, and head movements identified from facial video recordings. Emotional mouse collected measurements of heart rate, skin temperature, GSR and finger pressure, as well as the feature that capture interaction with the computer, such as the number of mouse clicks and pressure put on the mouse. They used dynamic Bayesian network to create a model with the collected data to classify users' stress conditions. In an experiment conducted to validate the model they created, they observed that when stress is decreased, participants clicked the mouse button more intensively, the heat rate increased and GSR decreased.

The study by Hernandez et al. [48] used a capacitive mouse in addition to the pressure-sensitive keyboard to detect variations of pressure applied on the mouse under different stress conditions. They used a mouse that had a grid of $13 \times 15$ capacitive pixels with values that range from 0 to 15 (no capacitance to maximum capacitance). They observed that while 75% participants applied more pressure on the mouse when they are under stress, rest of the participants reduced the pressure they applied on the mouse when stressed.

Qi et al. [95] reported a study where they measured mouse pressure signal of a computer user using eight pressure sensors mounted on a computer mouse. Data were collected under stress and under normal conditions, and used to build a classification model using Bayes point machine. The model achieved a classification accuracy of 88% when applied to detect stress condition of the participant.

Chigira et al. [32] presented the development of a PPG mouse that can be used to unobtrusively identify stress conditions of people. Their mouse measured the blood volume of fingers using a near-IR light and a photo-detector sensor attached to the mouse, and HRV features are extracted based on the collected data. They recommended that their method is a successful approach in identifying stress conditions via measuring BVP.

In a research conducted by Kaklauskas et al. [28], they developed an advisory system that allows users in making real-time measurements of their stress levels and provides suggestions to control the stress level. Their system used a biometric computer mouse that measured the temperature and moisture of the hand, skin conductance, touch intensity, and heart rate. Furthermore, it recorded the speed and the acceleration of the mouse pointer, the amount of hand shake, scroll wheel use, left-/right-click frequency, and idle time. Based on these inputs and users' self-reported stress levels, the system created a model of users' input variation with stress and provided an assessment of stress and recommendations based on them.

Samonte et al. [96] presented a study where they created a model to track emotions of gamers who play role playing games using their mouse movement data. They used a MouseKeyLogger program to collect data as the player was playing Torchlight 2 to monitor each player's mouse movements. Thereafter, 33 features, including mean mouse click duration (from button-down to button-up), and total duration of mouse clicks were extracted and separated in 15-s segments. Then, researchers created 12 models using RF, decision tree, J48 classifiers, and different subsets of extracted features. They claimed that their developed model can be used by game developers to determine various emotions of players while they are playing games.

Maehr [97] reported a research they conducted to investigate the influence of emotions on mouse movements. He recorded mouse movements of computer users while they are using a computer under two emotional conditions, happy and sad. The following features of mouse movements were extracted and studies in that study: acceleration, precision, smoothness, uniformity, and speed. Acceleration and deceleration were averaged over splitted movements. Precision was calculated by the ratio of clicks executed to the clicks required to successfully achieve a goal, or by the amount of movement required to hit a target. Movement smoothness was measured by considering the number of break of the movement and the variation of the average speed. Speed was measured by the average movements speed and also as the duration of clicks. Maehr [97] observed a significant influence of arousal for movement precision and smoothness measurements. Moreover, he observed that the number of clicks and movement discontinuities were affected by the arousal level of the participant.

There are several advantages and disadvantages into using mouse dynamic for stress detection. Similar to keystroke dynamics, recording mouse events does not require special hardware, is not intrusive, and is possible to record during usual computer use [92]. However, mouse dynamics also heavily depend on the hardware and software being used. For example, mouse measurements taken while using a computer game will be completely contrasting to those while using a text editor [92].

### I. Computer Use

Computer exposure of people is also a behavioral measure that can change according to the level of stress that they are experiencing. Eijckelhof et al. [98] reported a study where they attempted to investigate this relationship. They recorded keyboard and mouse usage details of office employees and used them to extract computer use duration, number of short and long computer breaks, and the rate of input equipment use. They observed that average daily computer usage duration was 30 minutes lengthier for subjects with high stress levels compared with subjects with low stress levels. It is hypothesized that computer games usage of people can reveal behavior patterns that can be used to detect stress. However, this hypothesis needs to be tested with careful experiment design, which is what the future work of this survey heading toward.

### J. Smart Phone Interactions

Data extracted from mobile phones, such as call logs, SMSes, e-mails, Internet browsing details, app's usage data, and location data, can tell many details about the user of the phone. Researchers have attempted to identify any patterns of these data that can be linked to stress conditions that the phone user is experiencing.

Muaremi et al. [99] reported a study they conducted to assess the work-related stress that someone is experiencing based on their mobile phone interaction data. They extracted three types of features from the collected mobile phone data of 35 participants, which are audio (>384 features), physical activity (four features), and social interaction (13 features). The classifier developed using five of these features, which are the number of calls, audio length, distance, speech energy, and mean call length, achieved a classification accuracy of 55%.

Sano et al. [100] also reported a study that attempted to detect stress of 18 individuals using their mobile phone usage data. They monitored calls, SMSes, location data, communication aspects, and screen ON/OFF events, and 351 features were extracted from this information. Results indicated that the ratio of sent SMSes to all sent and received SMSes decreased under high levels of stress. Furthermore, they observed that the screen ON/OFFpatterns changed, where the screen "ON" time reduced when the user is stressed. Both classification models developed with SVM and kNN algorithms that used mobile phone usage features achieved a classification accuracy of 87.5%.

In the study performed by Carneiro et al. [12] to investigate approaches of noninvasive stress detection, they collected data related to mobile phone usage of 19 participants. While participants are playing an arithmetic number game, data related to their touch pattern, touch accuracy, touch intensity, touch duration, amount of movement, and acceleration are collected. Statistical testing performed on the collected data revealed that acceleration and mean and maximum touch intensity depended on the stress that the participant was experiencing. Since smart phones are an everyday technology they have a capability to provide useful behavior data for stress detection.

### K. Performance

Many researchers have studied the consequences of stress on an individual's performance. As stated by the Yerkes–Dodson Law, when the arousal increases, performance is increased to a certain level and then decreases, following an inverted U-shaped curve [101].

In the stress-detection study performed by Liao et al. [44], they collected performance measurements by extracting error rate and response time for arithmetic and audio tasks. Their results showed that the rate of mistakes reduced, lexical and content diversity enhanced, and pause length reduced, showing an enhancement in performance when the stress is increased. However, they also observed an improvement in the normalized time per keystroke in the physical stress condition, indicating a descent in one component of performance. They concluded that the induced stress was only sufficient to positively influence performance without overwhelming the subject.

In addition, Blom et al. [102] suggested collecting in game logs of players who play League of Legends in order to assess their stress by identifying their postgame statistics and in-game events. Even though they expected scores to decrease under increased stress conditions, they have not reported the outcome of their study. This requires further research to investigate if performance in games can be used as a way to detect stress.

## VI. Multimodel Approach for Stress Detection

Even though we have discussed measurements for stress detection individually by separating them from other similar methods, the common trend is to use multiple stress measurements. Researchers highlight that variation of some of the discussed parameters are not caused only by stress change. Therefore, they recommend using multiple different types of measurements to detect stress more effectively [12], [13], [44]. Liao et al. [44] affirmed that the utility of this method has been exhibited by the increase of classification accuracy achieved by classifiers that use multiple measurements compared with classifiers that use a single stress measurement.

In the work conducted by Healey et al. [45], their model used data related to EMG, respiration, skin conductance, and heart rate. Their model achieved an accuracy of 97% for classifying data into three stress levels. Wijsman et al. [36] reported a stress-detection model they created using ECG, skin conductance, respiration, and EMG signals. Their model obtained an accuracy rate of 74.5%.

Schmidt et al. [103] presented a study where they used multiple types of parameters collected using sensors attached to wrist and chest of 15 users for stress detection. Using both types of sensors, they collected physiological and movement-related data of participants. They observed the best accuracy when the classification model is fed with all measurements (i.e., ECG, GSR, EMG respiration, and skin temperature) collected with the sensor attached to participants chest. This multiple measurement-based stress-detection model obtained an accuracy of 93.1% distinguishing stress from nonstress conditions. The dataset they used has been made available publicly by the authors.

Koldijk et al. [104] reported a study that used computer interaction, facial expression, body posture, GSR, and HRV to detect stress conditions of 25 individuals. They achieved an accuracy of 90% when used all types of measurements in the classification model. They reported that using a subset of these features always achieved a lower accuracy compared with using all measurements together.

Zhai and Barreto [33] also reported a study that used multiple measurements (i.e., GSR, BVP, pupil diameter, and skin temperature) for stress assessment. They used data collected from two participants. SVM-based classifier that used all four types of parameters achieved an accuracy of 90.1%. They observed that models created using three types of parameters instead of four always resulted in lesser accuracy values.

Bevilacqua et al. [78] performed a study where they used facial expressions and heart rate data for stress detection of computer game players. They observed that using both types of data for classification yields higher accuracy (62.3%) compared with using only one type of data.

## VII. Summary of Stress-Detection Methods

Table I summarizes the stress-detection methods discussed in Sections IV and V and their notable advantages and disadvantages. The invasive methods listed in the table requires complex procedures and professionals to analyze them. As such they are not suitable for day to day stress detection. The methods listed in the table as the invasive/obstructive methods requires direct contact with the subject and/or equipment to be fitted correctly. For example, EEG equipment needs to be worn correctly to obtain accurate brain signals. While some of these sensors are now available as low-cost, consumer grade sensors (as such can be available in home environments), it is not practical to use them for day to day stress monitoring. Methods 11–18 listed in Table I are relatively less intrusive/obstructive. However considering the environmental conditions, not all the methods listed are suitable for a home environment. Considering multiple factors such as the cost, intrusiveness, obstructiveness and environmental condition, Section VIII summarizes the stress-detection methods that can be used during day to day gameplay situations.

TABLE I
Summary of Stress-Detection Methods and Their Notable Advantages/Disadvantages

| | **Method** | **Notable advantages/ disadvantages** |
|---|---|---|
| 1 | Blood, Saliva, Urine | Invasive, Requires professionals |
| 2 | BP | Intrusive |
| 3 | BVP | Moderate accuracy, Could use less intrusively |
| 4 | ECG | High accuracy, Intrusive |
| 5 | EEG | High accuracy, Intrusive |
| 6 | GSR | Moderate-High Accuracy, Could use less intrusively |
| 7 | fMRI | Intrusive |
| 8 | EMG | High accuracy, obstructive |
| 9 | Respiration | Moderate accuracy, Intrusive |
| 10 | Skin temperature | Intrusive, Mixed results |
| 11 | Thermal Imaging | Depends on environmental conditions |
| 12 | Voice | Depends on environmental conditions |
| 13 | Eye Gaze, PD | Moderate-High Accuracy, less intrusive |
| 14 | Blink Rates | Mixed results |
| 15 | Facial Expressions | High Accuracy, Less intrusive |
| 16 | Gesture and movement | Requires special equipment |
| 17 | Keyboard, Mouse | Moderate-high accuracy, Less expensive |
| 18 | Smart phone Interaction | Everyday technology, Low-moderate accuracy |

## VIII. Stress-Detection Techniques During Gameplay

The motivation for this review is to identify the possibility of stress detection with the inputs that can be collected through gameplay. Therefore, this section will present a summary of methods that were discussed in previous sections and can be applied when someone plays a game considering the intrusiveness, obstructiveness, and conditions in home environments.

### A. Mobile Phone-Related Data

This review identified a few studies that detected stress using smart phone inputs while playing mobile games [12], [105] (see Section V-J). Interestingly, these appear to be the only studies that directly extracted data from gameplay inputs. Findings of this review suggest the possibility of designing mobile games to use data, such as touch pattern, touch accuracy, touch intensity, touch duration, acceleration, and player movement, to detect stress conditions of players.

### B. Keyboard-Related Data

Keyboard is a main input device that is used in gameplay. Section V-G of this review revealed different methods of leveraging data collected through keyboard for stress detection. This can be carried out using a normal keyboard where data related to keyboard typing patterns can be used for stress detection. In addition, literature reports the use of special types of pressure sensitive keyboards that can collect data related to the pressure applied by computer users in order to detect their stress conditions. Computer games can use both these methods in order to embed stress-detection functionalities into gameplay.

### C. Mouse-Related Data

Mouse is also vastly used as a input device in computer gameplay. Section V-H reviewed various methods that used inputs collected via a mouse for stress detection. Similar to keyboard-related data, mouse data can be collected from an ordinary computer mouse as well as from a especially designed mouse. A normal mouse can provide data, such as cursor movement-related data, click-related data, and scroll-related data, that can be utilized for stress identification. Furthermore, this review revealed especially designed mouses that are pressure sensitive and equipped with PPG functionalities that are especially designed for stress-detection purposes. Computer games can use both these types of data in order to embed stress-detection functionalities into gameplay.

### D. Game Controller-Related Data

Game controller is another common input device that is used during gameplay. This review does not reveal any game controller-based techniques that were used for stress detection. However, research by Abe et al. [106] presented a game controller embedded with PPG functionality that is capable of monitoring heart rate of game players. Since stress affects the heart rate of individuals, this suggests the applicability of collecting data with game controllers for stress detection.

### E. Gaming Performance and Affect Detection

Section V-K discussed the detection of stress using performance related data. This suggests the applicability of acquiring game performance related data during gameplay to detect stress levels of game player. However, since the ambiguity of observations related to the effect of stress on performance, more research is required to have a clear view on how game performance can be leveraged for stress detection.

Although not directly related to stress detection there have been multiple studies that have used computer games for emotion and affect detection, such as [78], [107], and [108]. The study in [78] has used heart rate and computer vision to detect user emotions in the context of games. However, the accuracy rate was only slightly better than chance. Camilleri et al. [107] shows how arousal can be mapped to gameplay and physiological features across three different games. The attempt was to demonstrate how computational models of affect are general in different tasks. It has been shown in [78] how student engagement in a prosocial game can be recognized by combining engagement cues from both students and game. Body motion and facial expressions were used to extract the engagement related features from the students and behavioral and cognitive engagement related features were extracted based on their interaction with the game (for example, average time of responsiveness). It is worthy to investigate if similar mechanisms can be used for stress detection via gameplay.

### F. Eye Gaze and PD Data

Section V-C discussed stress detection from eye gaze data as well as from gaze mouse coordination patterns. Furthermore, Section V-B presented stress-detection methods that used PD data. Both these methods appeared to achieve good accuracy rates when used for stress detection. These types of data can be collected from gamers while they are involved in gameplay for detecting stress.

TABLE II
A SUMMARY OF OBSTRUCTIVE METHODS

| Research paper | Input collection methods | Number of collected features | Number of subjects | Classification algorithm | Stress classification accuracy |
|---|---|---|---|---|---|
| De Santos Sierra et al. [47] | GSR, Heart Rate | - | 80 | Fuzzy logic | 99.5% |
| Wei et al. [49] | EMG | - | 45 | Fisher linear discriminant | 97.8% |
| Healey and Picard [45] | EMG, respiration, Heart Rate, GSR | 22 | 24 | SVM | 97% |
| Palanisamy et al. [37] | ECG | 5 | 40 | kNN | 93.8% |

### G. Voice and Speech

This review discussed how voice and speech are affected by stress and how they can be used for stress detection. Computer games can be designed to capture voice and speech data while they are interacting with games, especially, when players provide voluntary speech data while playing multiplayer games to communicate with fellow team mates. Therefore, voice and speech can be recognized as a data collection method that can be used to embed stress detection functionalities into computer games.

### H. Video Inputs

This review revealed the use of video inputs for detecting stress by capturing facial and behavioral features. Furthermore, it revealed the use of thermal imaging for detecting stress. Video capturing can be used to unobtrusively collect inputs from game players during gameplay to detect stress conditions of them.

### I. Posture

Section V-F presented a research by Arnrich et al. [79], where they detected stress levels of computer users using pressure sensors embedded to their chairs. This method can also be used to detect stress of game players. However, this requires a especially designed chair that can record pressure inputs.

## IX. DISCUSSION AND CONCLUSION

This review presented different stress-detection methods that have been proposed in the literature via various sensors. While the methods reviewed in Section IV are more obstructive and require various special equipments for stress detection, methods reviewed in Section V are less obstructive and can be performed with commonly available and cheaper equipment. Tables II and III summarize the studies, their input collection methods, number of subjects, classification algorithms used, and accuracy obtained for obstructive methods and less obstructive methods, respectively. Each table lists only four studies out of the reviewed

TABLE III
A Summary of Less Obstructive Methods That are Suitable for a Home Environment

| Research paper | Input collection methods | Number of collected features | Number of subjects | Classification algorithm | Stress classification accuracy |
|---|---|---|---|---|---|
| Gianaakakis et al. [75] | Facial expressions | 4 | 23 | AdaBoost | 91.7% |
| Ren et al. [66] | PD | 3 | 42 | Naive Bayes | 88.6% |
| Dinges et al. [71] | Facial expressions | - | 60 | Hidden Markov model | 75% - 88% |
| Vizer et al. [86] | Keystroke + Linguistic | 42 | 24 | KNN | 75% |

literature that have employed at least 20 subjects for evaluation in the descending order of accuracy. While there are some other studies showing competitive accuracy rates, due to the limited number of subjects employed in the studies, they were not included in the summary tables.

According to Table II, GSR and heart rate have shown the highest accuracy rate for a large pool of subjects. Out of the less obstructive methods, facial expressions have shown competitive accuracy rates. Other methods suitable for home environments show promising results in stress classification and detection, however, require more improvements to be used as a reliable technology. There are also some studies that have attempted to use reliable sensors in a less obstructive way (such as combining a GSR sensor with a mouse) [44].

Games, being a popular entertainment media all around the world, has a potential of being an effective technology in increasing people's health and wellbeing. Due to the nature of interactivity and the large amount of behavioral data that they can generate, games have the potential of identifying people's behavioral patterns that could assist in detecting various mental states including stress. This survey revealed very limited studies on stress detection during gameplay. However, the literature shows very promising directions toward this end. Due to the advancements in low-cost sensor technologies (such as eye trackers), stress-detection methods that can be used in home-based settings have been able to achieve reasonable accuracy rates when compared with more invasive sensors that can only be used in more artificial settings. These low-cost sensors when combined with a large amount of behavioral data produced by gameplay data has the potential of producing even more accurate determinations of people's stress states. This is particularly useful as a flagging/screening mechanism to seek professional medical intervention, provide objective data for medical professionals, or simply use as a trigger to change simple lifestyle choices that one has the control of. Mental health, being a major concern of the modern society, requires national intervention strategies to prevent more long term adverse impacts to the society. The unprecedented situation the world has faced due to the COVID-19 pandemic shows the need of such technologies even more now, because home isolation and quarantine requirements have significant impacts on people's mental health. This survey shows that games, being a media used in most of the households, have the potential of to being developed as a low cost and less obstructive technology to detect and monitor people's stress in day-to-day life.

Recent trends show that stress-detection studies are moving toward real-life situations [109]. Recent advancements in consumer grade wearable sensors are making this a reality. However, there are numerous challenges that need to be addressed in order to employ these consumer grade sensors in detecting stress reliably. These include incorrect placement of sensors, synchronization, limited battery time, and difficulty to establish a ground truth [110]. Use of behavioral data without explicit placement of sensors can overcome some of these challenges. For example, capturing game behavioral data through keyboard and mouse interactions will not require user to wear any special sensor requiring battery power. This could be complemented with a GSR sensor attached to the mouse, which has shown reliable stress detection results. In terms of machine learning techniques, recent studies have employed deep learning techniques for stress detection [111], [112]. Research shows that average players spend more than 6 h weekly playing games [1]. Gameplay of this length will generate a large amount of game behavioral data that are suitable for training deep learning models. This survey did not find studies that explore deep learning techniques for stress detection during gameplay. This is a promising research direction that can be explored to develop reliable stress-detection techniques during gameplay.

It is acknowledged that stress can be positive or negative. Particularly in the context of games, positive stress can occur and detecting positive stress will require different techniques and approaches. It is beyond the scope of this article to review the techniques and measures that can differentiate positive and negative stress. However, it is hypothesized that given other factors constant, stress responses for negative stress are different to the responses for positive stress. As such, detecting stress due to other life factors (negative stress) during gameplay using the aforementioned techniques is a promising research direction that needs to be backed by preliminary experimental results.

## X. Limitations of the Work

The categorization of stress-detection techniques for laboratory settings and home settings presented in this survey is not a strict categorization. Some of the techniques can be applied in both settings with adjustments. With the advancements of technology, it is also possible some sensors are becoming cheaper and more accurate, making them suitable for home settings. The motivation of the survey was to identify a subset of techniques that can be further explored in recognizing stress during gameplay. Finally, this survey did not consider recognizing eustress or making a differentiation between positive and negative stress as it is out of the scope of the survey.

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## REFERENCES


[1] Newzoo, "The global games market will generate $152.1 billion in 2019 as the U.S. overtakes China as the biggest market." Accessed: May 7, 2020. [Online]. Available: https://newzoo.com/insights/articles/the-global-games-market-will-generate-152-1-billion-in-2019-as-the-u-s-overtakes-china-as-the-biggest-market/

[2] L. Networks, "The state of online gaming 2020," Limelight Netw., Tempe, AZ, USA, 2020.

[3] S. Folkman, *Stress: Appraisal and Coping*. New York, NY, USA: Springer, 2013.

[4] A. Steptoe and M. Kivimäki, "Stress and cardiovascular disease: An update on current knowledge," *Annu. Rev. Public Health*, vol. 34, pp. 337–354, 2013.

[5] A. M. Heraclides, T. Chandola, D. R. Witte, and E. J. Brunner, "Work stress, obesity and the risk of Type 2 diabetes: Gender-specific bidirectional effect in the Whitehall II study," *Obesity*, vol. 20, no. 2, pp. 428–433, 2012.

[6] B. D'Angelo and M. Wierzbicki, "Relations of daily hassles with both anxious and depressed mood in students," *Psychol. Rep.*, vol. 92, no. 2, pp. 416–418, 2003.

[7] B. P. Parrish, L. H. Cohen, and J.-P. Laurenceau, "Prospective relationship between negative affective reactivity to daily stress and depressive symptoms," *J. Social Clin. Psychol.*, vol. 30, no. 3, pp. 270–296, 2011.

[8] D. Wannigamage, M. Barlow, E. Lakshika, and K. Kasmarik, "Analysis and prediction of player population changes in digital games during the Covid-19 pandemic," in *Proc. AI 2020: Adv. Artif. Intell.*, M. Gallagher, N. Moustafa, and E. Lakshika, Eds., 2020, pp. 458–469.

[9] J. R. Edwards, "A cybernetic theory of stress, coping, and well-being in organizations," *Acad. Manage. Rev.*, vol. 17, no. 2, pp. 238–274, 1992.

[10] C.-T. Li, J. Cao, and T. M. Li, "Eustress or distress: An empirical study of perceived stress in everyday college life," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.: Adjunct*, 2016, pp. 1209–1217.

[11] S. J. Lupien, F. Maheu, M. Tu, A. Fiocco, and T. E. Schramek, "The effects of stress and stress hormones on human cognition: Implications for the field of brain and cognition," *Brain Cogn.*, vol. 65, no. 3, pp. 209–237, 2007.

[12] D. Carneiro, J. C. Castillo, P. Novais, A. F.-Caballero, and J. Neves, "Multimodal behavioral analysis for non-invasive stress detection," *Expert Syst. Appl.*, vol. 39, no. 18, pp. 13376–13389, 2012.

[13] A. Alberdi, A. Aztiria, and A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review," *J. Biomed. Inform.*, vol. 59, pp. 49–75, 2016.

[14] T. Hayashi, Y. M.-Matsumoto, E. Okamoto, M. Kato, and T. Murata, "An FMRI study of brain processing related to stress states," in *Proc. IEEE World Autom. Congr.*, 2012, pp. 1–6.

[15] S. Cohen, T. Kamarck, and R. Mermelstein, "Perceived stress scale," in *Measuring Stress: A Guide for Health and Social Scientists.* New York, NY, USA: Oxford Univ. Press, 1994, pp. 1–2.

[16] K. B. Koh, J. K. Park, and C. H. Kim, "Development of the stress response inventory," *J. Korean Neuropsychiatric Assoc.*, vol. 39, no. 4, pp. 707–719, 2000.

[17] S.-H. Seo and J.-T. Lee, "Stress and EEG," *Convergence Hybrid Inf. Technol.*, vol. 1, no. 1, pp. 413–424, 2010.

[18] C. Wohlin, "Guidelines for snowballing in systematic literature studies and a replication in software engineering," in *Proc. 18th Int. Conf. Eval. Assessment Softw. Eng.*, 2014, pp. 1–10.

[19] Nvivo, "Qualitative data analysis software: Nvivo." Accessed: Jun. 15, 2021. [Online]. Available: https://www.qsrinternational.com/nvivo-qualitative-data-analysis-software/home/

[20] S. Choi, S. Kim, J.-S. Yang, J.-H. Lee, C. Joo, and H.-I. Jung, "Real-time measurement of human salivary cortisol for the assessment of psychological stress using a smartphone," *Sens. Bio-Sensing Res.*, vol. 2, pp. 8–11, 2014.

[21] P. Jin, "Efficacy of Tai Chi, brisk walking, meditation, and reading in reducing mental and emotional stress," *J. Psychosomatic Res.*, vol. 36, no. 4, pp. 361–370, 1992.

[22] J. S. Lerner, R. E. Dahl, A. R. Hariri, and S. E. Taylor, "Facial expressions of emotion reveal neuroendocrine and cardiovascular stress responses," *Biol. Psychiatry*, vol. 61, no. 2, pp. 253–260, 2007.

[23] U. Lundberg et al., "Psychophysiological stress and EMG activity of the trapezius muscle," *Int. J. Behav. Med.*, vol. 1, no. 4, pp. 354–370, 1994.

[24] F. E. Ritter, R. Ceballos, A. Reifers, and L. C. Klein, "Measuring the effect of dental work as a stressor on cognition," University Park, PA, USA, 2005. [Online]. Available: http://act-r.psy.cmu.edu/wordpress/wp-content/themes/ACT-R/misc/ritter.ppt

[25] N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition and classification: A survey," *Comput. Methods Programs Biomed.*, vol. 108, no. 3, pp. 1287–1301, 2012.

[26] B. Netterstrøm, L. Danborg, and H. Olesen, "Glycated hemoglobin as a measure of physiological stress," *Behav. Med.*, vol. 14, no. 1, pp. 13–16, 1988.

[27] T. G. Pickering, "Principles and techniques of blood pressure measurement," *Cardiol. Clin.*, vol. 20, no. 2, pp. 207–223, 2002.

[28] A. Kaklauskas et al., "Web-based biometric computer mouse advisory system to analyze a user's emotions and work productivity," *Eng. Appl. Artif. Intell.*, vol. 24, no. 6, pp. 928–945, 2011.

[29] T. G. Pickering et al., "Environmental influences on blood pressure and the role of job strain," *J. Hypertens. Suppl.*, vol. 14, no. 5, pp. S179–S185, 1996.

[30] N. Hjortskov, D. Rissén, A. K. Blangsted, N. Fallentin, U. Lundberg, and K. Søgaard, "The effect of mental stress on heart rate variability and blood pressure during computer work," *Eur. J. Appl. Physiol.*, vol. 92, no. 1/2, pp. 84–89, 2004.

[31] S. Reisman, "Measurement of physiological stress," in *Proc. IEEE 23rd Northeast Bioeng. Conf.*, 1997, pp. 21–23.

[32] H. Chigira, M. Kobayashi, and A. Maeda, "Mouse with photo-plethysmographic surfaces for unobtrusive stress monitoring," in *Proc. IEEE 2nd Int. Conf. Consum. Electron.-Berlin*, 2012, pp. 304–305.

[33] J. Zhai and A. Barreto, "Stress detection in computer users based on digital signal processing of noninvasive physiological variables," in *Proc. IEEE Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2006, pp. 1355–1358.

[34] D. McDuff, S. Gontarek, and R. Picard, "Remote measurement of cognitive stress via heart rate variability," in *Proc. IEEE 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2014, pp. 2957–2960.

[35] E. J. Berbari, "Principles of electrocardiography," *Biomed. Eng. Handbook*, vol. 1, pp. 13–11, 2000.

[36] J. Wijsman, B. Grundlehner, H. Liu, J. Penders, and H. Hermens, "Wearable physiological sensors reflect mental stress state in office-like situations," in *Proc. IEEE Humaine Assoc. Conf. Affect. Comput. Intell. Interact.*, 2013, pp. 600–605.

[37] K. Palanisamy, M. Murugappan, and S. Yaacob, "Multiple physiological signal-based human stress identification using non-linear classifiers," *Elektronika ir Elektrotechnika*, vol. 19, no. 7, pp. 80–85, 2013.

[38] S. Vandeput, J. Taelman, A. Spaepen, and S. Van Huffel, "Heart rate variability as a tool to distinguish periods of physical and mental stress in a laboratory environment," in *Proc. 6th Int. Workshop Biosignal Interpretation (BSI)*, 2009, pp. 187–190.

[39] B. Cinaz, B. Arnrich, R. La Marca, and G. Tröster, "Monitoring of mental workload levels during an everyday life office-work scenario," *Pers. Ubiquitous Comput.*, vol. 17, no. 2, pp. 229–239, 2013.

[40] C.-K. A. Lim and W. C. Chia, "Analysis of single-electrode EEG rhythms using MATLAB to elicit correlation with cognitive stress," *Int. J. Comput. Theory Eng.*, vol. 7, no. 2, p. 149–155, 2015.

[41] D. Das, T. Bhattacharjee, S. Datta, A. D. Choudhury, P. Das, and A. Pal, "Classification and quantitative estimation of cognitive stress from in-game keystroke analysis using EEG and GSR," in *Proc. IEEE Life Sci. Conf. (LSC)*, 2017, pp. 286–291.

[42] E. A. Schoneveld, M. Malmberg, A. L.-Aschoff, G. P. Verheijen, R. C. Engels, and I. Granic, "A neurofeedback video game (mindlight) to prevent anxiety in children: A randomized controlled trial," *Comput. Hum. Behav.*, vol. 63, pp. 321–333, 2016.

[43] H. Zhang, Y. Zhu, J. Maniyeri, and C. Guan, "Detection of variations in cognitive workload using multi-modality physiological sensors and a large margin unbiased regression machine," in *Proc. IEEE 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2014, pp. 2985–2988.

[44] W. Liao, W. Zhang, Z. Zhu, and Q. Ji, "A real-time human stress monitoring system using dynamic Bayesian network," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. -Workshops*, 2005, pp. 70–70.

[45] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005.

[46] A. Sinha, P. Das, R. Gavas, D. Chatterjee, and S. K. Saha, "Physiological sensing based stress analysis during assessment," in *Proc. IEEE Front. Educ. Conf.*, 2016, pp. 1–8.

[47] A. de S. Sierra, C. S. Ávila, G. B. del Pozo, and J. G. Casanova, "Stress detection by means of stress physiological template," in *Proc. IEEE 3rd World Congr. Nature Biol. Inspired Comput.*, 2011, pp. 131–136.

[48] J. Hernandez, P. Paredes, A. Roseway, and M. Czerwinski, "Under pressure: Sensing stress of computer users," in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, 2014, pp. 51–60.

[49] C. Z. Wei, “Stress emotion recognition based on RSP and EMG signals,” *Proc. Adv. Mater. Res.*, vol. 709, pp. 827–831, 2013.

[50] H. Kataoka, H. Kano, H. Yoshida, A. Saijo, M. Yasuda, and M. Osumi, “Development of a skin temperature measuring system for non-contact stress evaluation,” in *Proc. 20th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.,*1998, pp. 940–943.

[51] K. Asai, “The role of head-up display in computer-assisted instruction,” in *Human Computer Interaction: New Developments*; K. Asai, Ed., Rijeka, Croatia: IntechOpen, pp. 31–48, 2008.

[52] S. Begum, M. U. Ahmed, P. Funk, N. Xiong, and B. V. Schéele, “Using calibration and fuzzification of cases for improved diagnosis and treatment of stress,” in *Proc. 8th Eur. Workshop Case-based Reasoning Health Sci.*, 2006, pp. 113–122.

[53] J. A. Levine, I. T. Pavlidis, L. MacBride, Z. Zhu, and P. Tsiamyrtzis, “Description and clinical studies of a device for the instantaneous detection of office-place stress,” *Work*, vol. 34, no. 3, pp. 359–364, 2009.

[54] M. N. H. Mohd, M. Kashima, K. Sato, and M. Watanabe, “Facial visual-infrared stereo vision fusion measurement as an alternative for physiological measurement,” *J. Biomed. Image Process. (JBIP)*, vol. 1, no. 1, pp. 34–44, 2014.

[55] N. Sharma, A. Dhall, T. Gedeon, and R. Goecke, “Thermal spatio-temporal data for stress recognition,” *EURASIP J. Image Video Process.*, vol. 2014, no. 1, 2014, Art. no. 28.

[56] I. R. Murray, C. Baber, and A. South, “Towards a definition and working model of stress and its effects on speech,” *Speech Commun.*, vol. 20, no. 1/2, pp. 3–12, 1996.

[57] P. Wittels, B. Johannes, R. Enne, K. Kirsch, and H.-C. Gunga, “Voice monitoring to measure emotional load during short-term stress,” *Eur. J. Appl. Physiol.*, vol. 87, no. 3, pp. 278–282, 2002.

[58] C. E. Williams, “On determining the emotional states of pilots during flight: An exploratory study,” *Aerosp. Med.*, vol. 40, pp. 1369–1372, 1969.

[59] T. L. Nwe, S. W. Foo, and L. C. D. Silva, “Speech emotion recognition using hidden Markov models,” *Speech Commun.*, vol. 41, no. 4, pp. 603–623, 2003.

[60] K. Gopalan, “On the effect of stress on certain modulation parameters of speech,” in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., Proc. (Cat. No 01CH37221)*, 2001, pp. 101–104.

[61] H. Lu et al., “Stresssense: Detecting stress in unconstrained acoustic environments using smartphones,” in *Proc. ACM Conf. Ubiquitous Comput.*, 2012, pp. 351–360.

[62] G. Demenko and M. Jastrzebska, “Analysis of voice stress in call centers conversations,” in *Proc. Speech Prosody*, 2012, pp. 183–186.

[63] H. Kurniawan, A. V. Maslov, and M. Pechenizkiy, “Stress detection from speech and Galvanic skin response signals,” in *Proc. 26th IEEE Int. Symp. Comput.-Based Med. Syst.*, 2013, pp. 209–214.

[64] A. Barreto, J. Zhai, and M. Adjouadi, “Non-intrusive physiological monitoring for automated stress detection in human-computer interaction,” in *Proc. Int. Workshop Hum.- Comput. Interact.*, 2007, pp. 29–38.

[65] K. Sakamoto, S. Aoyama, S. Asahara, H. Mizushina, and H. Kaneko, “Relationship between emotional state and pupil diameter variability under various types of workload stress,” in *Proc. Int. Conf. Ergonom. Health Aspects Work Comput.*, 2009, pp. 177–185.

[66] P. Ren, A. Barreto, J. Huang, Y. Gao, F. R. Ortega, and M. Adjouadi, “Off-line and on-line stress detection through processing of the pupil diameter signal,” *Ann. Biomed. Eng.*, vol. 42, no. 1, pp. 162–176, 2014.

[67] M. X. Huang, J. Li, G. Ngai, and H. V. Leong, “Stressclick: Sensing stress from gaze-click patterns,” in *Proc. 24th ACM Int. Conf. Multimedia*, 2016, pp. 1395–1404.

[68] J. Wang, M. X. Huang, G. Ngai, and H. V. Leong, “Are you stressed? Your eyes and the mouse can tell,” in *Proc. IEEE 7th Int. Conf. Affect. Comput. Intell. Interact. (ACII)*, 2017, pp. 222–228.

[69] J. Wang, E. Y. Fu, G. Ngai, H. V. Leong, and M. X. Huang, “Detecting stress from mouse-gaze attraction,” in *Proc. 34th ACM/SIGAPP Symp. Appl. Comput.*, 2019, pp. 692–700.

[70] M. Haak, S. Bos, S. Panic, and L. Rothkrantz, “Detecting stress using eye blinks and brain activity from EEG signals,” in *Proc. 1st Driver Car Interact. Interface*, 2009, pp. 35–60.

[71] D. F. Dinges et al., “Optical computer recognition of facial expressions associated with stress induced by performance demands,” *Aviation, Space, Environ. Med.*, vol. 76, no. 6, pp. B172–B182, 2005.

[72] S. Dubuisson, F. Davoine, and M. Masson, “A solution for facial expression representation and recognition,” *Signal Process.: Image Commun.*, vol. 17, no. 9, pp. 657–673, 2002.

[73] J. Susskind, G. Littlewort, M. Bartlett, J. Movellan, and A. Anderson, “Human and computer recognition of facial expressions of emotion,” *Neuropsychologia*, vol. 45, no. 1, pp. 152–162, 2007.

[74] D. F. Dinges, S. Venkataraman, E. L. McGlinchey, and D. N. Metaxas, “Monitoring of facial stress during space flight: Optical computer recognition combining discriminative and generative methods,” *Acta Astronautica*, vol. 60, no. 4–7, pp. 341–350, 2007.

[75] G. Giannakakis et al., “Stress and anxiety detection using facial cues from videos,” *Biomed. Signal Process. Control*, vol. 31, pp. 89–101, 2017.

[76] J. Aigrain, S. Dubuisson, M. Detyniecki, and M. Chetouani, “Person-specific behavioural features for automatic stress detection,” in *Proc. 11th IEEE Int. Conf. Workshops Autom. Face Gesture Recognit. (FG)*, 2015, pp. 1–6.

[77] S. Das and K. Yamada, “Evaluating instantaneous psychological stress from emotional composition of a facial expression,” *J. Adv. Comput. Intell. Intell. Inform.*, vol. 17, no. 4, pp. 480–492, 2013.

[78] F. Bevilacqua, H. Engström, and P. Backlund, “Game-calibrated and user-tailored remote detection of stress and boredom in games,” *Sensors*, vol. 19, no. 13, 2019, Art. no. 2877.

[79] B. Arnrich, C. Setz, R. L. Marca, G. Tröster, and U. Ehlert, “What does your chair know about your stress level,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 207–214, Mar. 2010.

[80] Tekscan, “Conformat system,” Accessed: Jul. 24, 2022. [Online]. Available: https://www.tekscan.com/products-solutions/systems/conformat-system

[81] C. Epp, M. Lippold, and R. L. Mandryk, “Identifying emotional states using keystroke dynamics,” in *Proc. SIGCHI Conf. Hum. factors Comput. Syst.*, 2011, pp. 715–724.

[82] F. Bergadano, D. Gunetti, and C. Picardi, “Identity verification through dynamic keystroke analysis,” *Intell. Data Anal.*, vol. 7, no. 5, pp. 469–496, 2003.

[83] P. S. Dowland and S. M. Furnell, “A long-term trial of keystroke profiling using digraph, trigraph and keyword latencies,” in *Proc. IFIP Int. Inf. Secur. Conf.*, 2004, pp. 275–289.

[84] R. Joyce and G. Gupta, “Identity authentication based on keystroke latencies,” *Commun. ACM*, vol. 33, no. 2, pp. 168–176, 1990.

[85] F. Monrose and A. D. Rubin, “Keystroke dynamics as a biometric for authentication,” *Future Gener. Comput. Syst.*, vol. 16, no. 4, pp. 351–359, 2000.

[86] L. M. Vizer, L. Zhou, and A. Sears, “Automated stress detection using keystroke and linguistic features: An exploratory study,” *Int. J. Hum.-Comput. Stud.*, vol. 67, no. 10, pp. 870–886, 2009.

[87] M. Rodrigues, S. Gonçalves, D. Carneiro, P. Novais, and F. F.-Riverola, “Keystrokes and clicks: Measuring stress on e-learning students,” in *Management Intelligent Systems*. Berlin, Germany: Springer, 2013, pp. 119–126.

[88] M. Gomes, T. Oliveira, F. Silva, D. Carneiro, and P. Novais, “Establishing the relationship between personality traits and stress in an intelligent environment,” in *Proc. Int. Conf. Ind., Eng. Other Appl. Appl. Intell. Syst.*, 2014, pp. 378–387.

[89] A. Alhothali, “Modeling user affect using interaction events,” Master’s thesis, Univ. Waterloo, Waterloo, ON, Canada, 2011.

[90] P. Khanna and M. Sasikumar, “Recognising emotions from keyboard stroke pattern,” *Int. J. Comput. Appl.*, vol. 11, no. 9, pp. 1–5, 2010.

[91] H.-R. Lv, Z.-L. Lin, W.-J. Yin, and J. Dong, “Emotion recognition based on pressure sensor keyboards,” in *Proc. IEEE Int. Conf. Multimedia Expo*, 2008, pp. 1089–1092.

[92] A. Kołakowska, “A review of emotion recognition methods based on keystroke dynamics and mouse movements,” in *Proc. IEEE 6th Int. Conf. Hum. Syst. Interact. (HSI)*, 2013, pp. 548–555.

[93] S. S.-Majadas, O. C. Santos, and J. G. Boticario, “An evaluation of mouse and keyboard interaction indicators towards non-intrusive and low cost affective modeling in an educational context,” *Procedia Comput. Sci.*, vol. 35, pp. 691–700, 2014.

[94] R. V. Yampolskiy and V. Govindaraju, “Behavioural biometrics: A survey and classification,” *Int. J. Biometrics*, vol. 1, no. 1, pp. 81–113, 2008.

[95] Y. Qi, C. Reynolds, and R. W. Picard, “The Bayes point machine for computer-user frustration detection via pressuremouse,” in *Proc. Workshop Perceptive User Interfaces*, 2001, pp. 1–5.

[96] M. J. C. Samonte, L. A. Vea, R. M. C. S. Jose, A. J. V. Lagoy, C. E. P. Manlapid, and A. M. P. Perez, “An affect detector model for gamers on a role-playing game through mouse movements,” in *Proc. IEEE Int. Conf. Inf. Commun. Technol. Convergence (ICTC)*, 2018, pp. 489–494.

[97] W. Maehr, eMotion: Estimation of the User’s Emotional State by Mouse Motions. Saarbrücken, Germany: VDM Verlag, 2005.

[98] B. H. Eijckelhof et al., "Office workers' computer use patterns are associated with workplace stressors," *Appl. Ergonom.*, vol. 45, no. 6, pp. 1660–1667, 2014.
[99] A. Muaremi, B. Arnrich, and G. Tröster, "Towards measuring stress with smartphones and wearable devices during workday and sleep," *BioNanoScience*, vol. 3, no. 2, pp. 172–183, 2013.
[100] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in *Proc. IEEE Humaine Assoc. Conf. Affect. Comput. Intell. Interact.*, 2013, pp. 671–676.
[101] R. M. Yerkes and J. D. Dodson, "The relation of strength of stimulus to rapidity of habit-formation," *J. Comp. Neurol. Psychol.*, vol. 18, no. 5, pp. 459–482, 1908.
[102] P. M. Blom, S. Bakkes, and P. Spronck, "Towards multimodal stress response modelling in competitive league of legends," in *Proc. IEEE Conf. Games (CoG)*, 2019, pp. 1–4.
[103] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. V. Laerhoven, "Introducing WESAD, a multimodal dataset for wearable stress and affect detection," in *Proc. 20th ACM Int. Conf. Multimodal Interact.*, 2018, pp. 400–408.
[104] S. Koldijk, M. A. Neerincx, and W. Kraaij, "Detecting work stress in offices by combining unobtrusive sensors," *IEEE Trans. Affect. Comput.*, vol. 9, no. 2, pp. 227–239, Apr.–Jun. 2018.
[105] M. Gomes, T. Oliveira, D. Carneiro, P. Novais, and J. Neves, "Extracting behavioural patterns from a negotiation game," in *Proc. Int. Conf. Practical Appl. Agents Multi-Agent Syst.*, 2013, pp. 304–315.
[106] E. Abe, H. Chigira, K. Fujiwarai, T. Yamakawa, and M. Kano, "Heart rate monitoring by a pulse sensor embedded game controller," in *Proc. IEEE Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA)*, 2015, pp. 1266–1269.
[107] E. Camilleri, G. N. Yannakakis, and A. Liapis, "Towards general models of player affect," in *Proc. IEEE Seventh Int. Conf. Affect. Comput. Intell. Interact. (ACII)*, 2017, pp. 333–339.
[108] A. Psaltis, K. C. Apostolakis, K. Dimitropoulos, and P. Daras, "Multimodal student engagement recognition in prosocial games," *IEEE Trans. Games*, vol. 10, no. 3, pp. 292–303, Sep. 2018.
[109] K. Kyriakou et al., "Detecting moments of stress from measurements of wearable physiological sensors," *Sensors*, vol. 19, no. 17, 2019, Art. no. 3805.
[110] Y. S. Can, N. Chalabianloo, D. Ekiz, and C. Ersoy, "Continuous stress detection using wearable sensors in real life: Algorithmic programming contest case study," *Sensors*, vol. 19, no. 8, 2019, Art. no. 1849.
[111] R. Li and Z. Liu, "Stress detection using deep neural networks," *BMC Med. Inform. Decis. Making*, vol. 20, no. 11, pp. 1–10, 2020.
[112] M. N. Rastgoo, B. Nakisa, F. Maire, A. Rakotonirainy, and V. Chandran, "Automatic driver stress level classification using multimodal deep learning," *Expert Syst. Appl.*, vol. 138, 2019, Art. no. 112793.