This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2021.Doi Number

A Systematic Review of Sensing and Differentiating Dichotomous Emotional States Using Audio-Visual Stimuli

YEDUKONDALA RAO VEERANKI[1], HIMANSHU KUMAR[1], NAGARAJAN GANAPATHY[1,2], MEMBER, IEEE, BALASUBRAMANIAM NATARAJAN[3], SENIOR MEMBER, IEEE, AND RAMAKRISHNAN SWAMINATHAN[1], MEMBER, IEEE

[1] Biomedical Engineering Group, Department of Applied Mechanics, Indian Institute of Technology Madras, Chennai, Tamil Nadu, India
[2] Peter L. Reichertz Institute for Medical Informatics of TU Braunschweig and Hannover Medical School, Braunschweig, Germany
[3] Mike Wiegers Department of Electrical and Computer Engineering, Kansas State University, Manhattan, KS 66502

Corresponding author: Yedukondala Rao Veeranki (e-mail: ykraoveeranki@gmail.com).

This work did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ABSTRACT Recognition of dichotomous emotional states such as happy and sad play important roles in many aspects of human life. Existing literature has recorded diverse attempts in extracting physiological and non-physiological traits to record these emotional states. Selection of the right instrumental approach for measuring these traits plays a critical role in emotion recognition. Moreover, various stimuli have been used to induce emotions. Therefore, there is a current need to perform a comprehensive overview of instrumental approaches and their outcomes for the new generation of researchers. In this direction, this study surveys the instrumental approaches in discriminating happy and sad emotional states that are elicited using audio-visual stimuli. A comprehensive literature review is performed using PubMed, Scopus, and ACM digital library repositories. The reviewed articles are classified with respect to the i) stimulation modality, ii) acquisition protocol, iii) instrumentation approaches, iv) feature extraction, and v) classification methods. In total, 39 research articles were published on the selected topic of instrumental approaches in differentiating dichotomous emotional states using audio-visual stimuli between January 2011 and April 2021. The majority of the papers used physiological traits, namely electrocardiogram, electrodermal activity, heart rate variability, photoplethysmogram, and electroencephalogram based instrumental approaches for recognizing the emotional states. The results show that only a few articles have focused on audio-visual stimuli for the elicitation of happy and sad emotional states. This review is expected to seed research in the areas of standardization of protocols, enhancing the diagnostic relevance of these instruments, and extraction of more reliable biomarkers.

INDEX TERMS Audio-visual stimuli, classification, emotion recognition, happy, instrumentation, sad.

I. INTRODUCTION

Emotions are the fundamental intellectual capacity of humans characterized by perception, attention, and behavioral outcomes [1]. The six distinct universal emotions, namely disgust, sadness, happiness, fear, anger, surprise, have been classified by psychological research [2]. The emotions can be perceived as either positive or negative [3]. Positive emotions such as happiness, surprise, and anger are pleasant feelings, and negative emotions such as disgust, fear, and sadness are unpleasant to experience [3], [4]. Hence, the positive and negative emotions are considered diametric opposites [5]. Among these emotions, happiness and sadness are frequently experienced by humans, which is also called a core affect [2], [6]. In general, happiness appears to be the opposite of sadness and differs in nearly every aspect, such as behavior, body movements, facial expression, and brain activity [7], [8].

Happiness is associated with prosocial behavior, physical well-being, problem-solving, attention, confidence, life satisfaction, better health outcomes, and longevity [4], [9]–[12]. On the other hand, sadness is related to disappointment, mental pain, melancholy, and weakness [13]. Sadness is also related to many adverse effects, including depression, sleep disorders, anxiety, suicidal attempts, and scant attention.

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Long-term sadness has negative implications for cardiovascular activity [14]–[16]. Identification of these disorders at the earlier stage can help to improve treatment. Recently, a report on world happiness has also demanded significant attention to happiness [17]. Therefore, it is necessary to understand the neurological, psychiatrical, and biobehavioural mechanisms of happy and sad emotions.

This work is motivated by the growing interest in recognition of clinical conditions linked to happy and sad emotional states, such as prediction of major depressive disorder (MDD) in long-term sadness. Prolonged sadness is the precursor of MDD. The effect of MDD may lead to reduced quality of life. MDD is predicted to become the leading cause of disability by 2030 for around 20 percent of the population over the course of life [18]. In the current study, we consider the comparison of instrumental and physiological trait-based approaches available to recognize happy and sad emotional states, which may help to predict the clinical conditions.

The emotions are described using two common and popular ways, namely a discrete emotion approach and a dimensional approach. In a discrete emotion approach, emotions are categorized into six basic emotions, as described above. In a dimensional approach, the emotions are described using valence and arousal dimensions [19], [20]. The dimension of valence is the positive or negative emotion perceived by the users. In contrast, the dimension of arousal is the intensity of the particular emotion experienced by the users [21]. Happiness and sadness are described by clearly opposite valence and arousal levels [7], [22].

An emotional state can be characterized by both non-physiological and physiological trait-based approaches. Methods such as body movements, speech patterns, and facial expressions are used as a non-physiological trait-based approach [21], [23]. Conversely, the physiological signals such as Heart Rate Variability (HRV), Electrocardiogram (ECG), Photoplethysmogram (PPG), Electroencephalogram (EEG), facial Electromyography (fEMG), Electrodermal Activity (EDA), and, Respiration (RSP) are considered [24]–[29].

In a non-physiological trait, namely GAIT cycle, the movement of the body tends to incline forward and direct their hands towards their source of irritation in sadness. There is also a reduction in walking speed, vertical head motions, and arm swing in people that are perceived to be in a sad emotional state. The shoulder and elbow movement magnitudes are comparatively reduced in the sad emotional state [30]–[33].

In physiological traits, variations are observed in the amplitude and frequency of the signals. For example, ECG shows significant variations in the ST segment corresponding to happy and sad emotional states. The convex ST segment is highly predictive of a happy emotion state, while a concave ST elevation strongly suggests a sad emotional state [34]. For sad emotional states, sympathetic activation is reported to be high as compared to happiness [35], [36]. Moreover, in a sad state, HR increases to provide an increase in blood supply [37]. The variation in the HRV is inversely correlated with HR. Thus, HRV decreases in sadness, and it increases in happiness [38]. In a happy emotional state, the mouth muscle, zygomaticus, eye muscle, and orbicularis are activated and lead to a rise in the mouth corners. These muscle activities are reflected by fEMG [39], [40]. Also, the pulse beat cycle of the PPG signal is reported to be more significant for the happiness emotion state [41], [42].

In a happy emotional state, the brain regions such as the right frontal cortex, the precuneus, and the left insula are activated; whereas, in a sad state, there is an increase in activity of the brain regions, namely the left insula, the right occipital lobe, the left thalamus, the hippocampus, and the amygdala. The hippocampus is strongly linked with memory, and it makes sense that awareness of specific memories is associated with sad feelings [13], [43], [44]. These changes in the Central Nervous System activity are reflected in EEG.

EDA is a measure of the continuous variation in electrical property of human skin, which reflects the sympathetic division activity of the autonomic nervous system [45]–[47]. It is reported that the sweat expelled through the sweat glands is more in happiness than sadness. Thus, the conductance of EDA is higher in happiness as compared to sadness [48], [49].

Researchers have proposed various emotional triggers for the understanding of mental or cognitive processes. Especially, standardized collections of words, pictures, faces, and film clips/audio-visual stimuli have enabled research in affective computing by allowing the researchers to select suitable stimuli and compare the results through lab environments [50], [51]. The audio-visual stimuli are the important triggers to evoke intense emotional reactions in the laboratory because of their high resemblance to real emotional experiences [51]–[54].

Several physiological signals and non-physiological traits have been employed for differentiating dichotomous emotional states [39], [42], [55]–[91]. Although various literature has been reported, a systematic review that deals specifically with the happy and sad emotional states using audio-visual stimuli and a description on the instrumental approaches to classify them remains limited. The review also pinpoints the advantages, limitations, and gaps that exist in the instrumentation-based dichotomous emotion recognition field. In addition, it could contribute to the development of a standardized data collection protocol and assessment procedures for this field to evaluate different data acquisition methods.

II. REVIEW METHODOLOGY

This review methodology is divided into seven sub-sections, namely search strategy, subject information, stimulation modality, data acquisition protocol, instrumentation approach, feature extraction, and classification.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

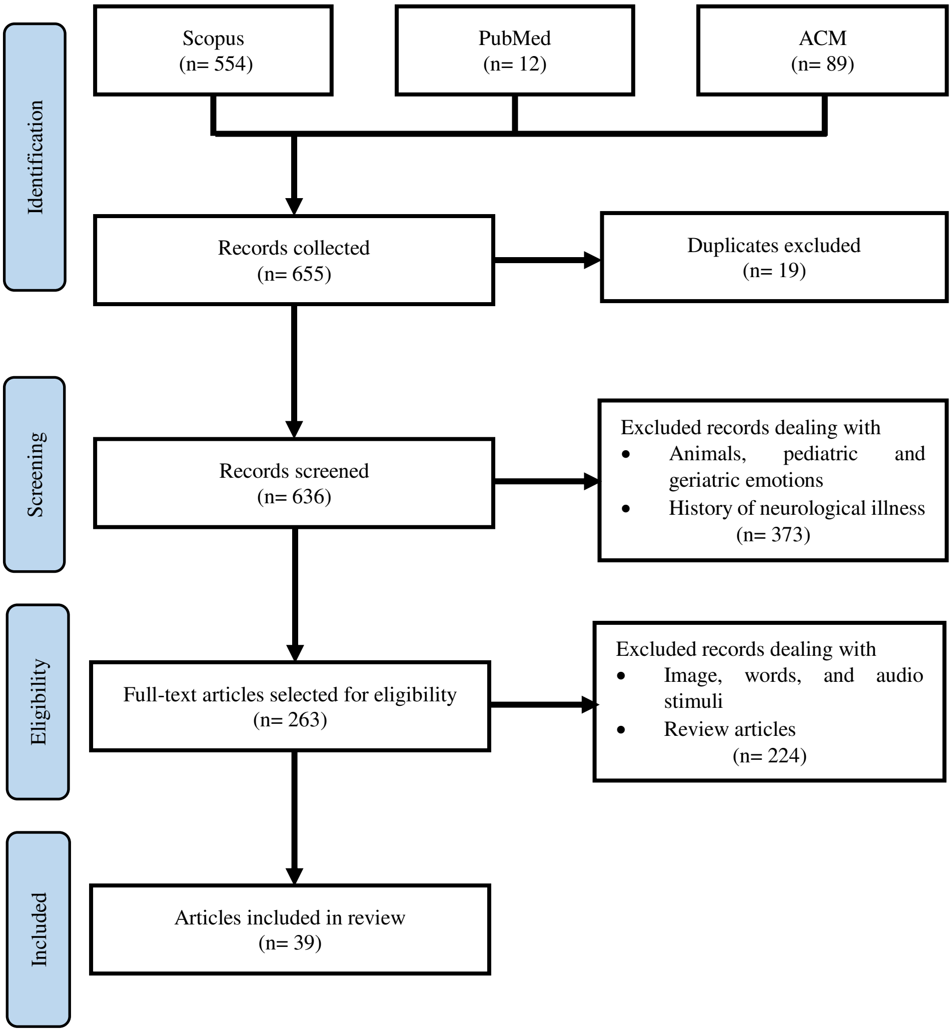

FIGURE 1. **PRISMA flowchart of the article selection process.**

A. SEARCH STRATEGY

The articles are obtained from the scientific repositories, namely Scopus, PubMed, and Association for Computing Machinery (ACM) digital library, from 01/01/2011 to 30/04/2021. To identify relevant articles, the selection process followed the PRISMA guidelines [92]. The search terms and phrases used are: ("emotion" OR "mood" OR "affect") AND ("happy" OR "happiness" OR "joy" OR "positive emotion" OR "valence") AND ("sad" OR "sadness" OR "negative emotion") AND ("audio-visual" OR "video" OR "film") AND ("electroencephalogram" OR "EEG signal" OR "electrocardiogram" OR "ECG signal" OR "electromyogram" OR "EMG signal" OR "electrodermal activity" OR "EDA signal" OR "galvanic skin response" OR "GSR signal" OR "photoplethysmogram" OR "PPG signal" OR "skin temperature" OR "GAIT") AND NOT ("anger" OR "disgust" OR "surprise").

A total of 655 articles (Scopus, n = 554; PubMed, n = 12; ACM, n = 89) are identified after the initial search process, and 19 articles have been omitted as duplicates. The screening phase involved the examination of records identified in the initial search. The query syntax is reviewed independently by two reviewers. Out of 636 articles, 373 articles are excluded based on the emotions related to animals, robots, pediatric, geriatric, and the participants with neurological disorders. Further, 224 studies have also been excluded after reviewing full-text articles based on the type of stimuli and research articles. Finally, 39 articles are included for the review. The inclusion criteria of articles are as follows: (i) studies using audio-visual stimuli for emotion elicitation (ii) studies differentiating only happy and sad emotional states, (iii) studies differentiating positive and negative emotional states, and (iv) studies with the combination of other emotional states, where happy and sad emotional states are classified discretely. The articles that does not include happy and sad emotional states in their methodology are excluded. The PRISMA flowchart used for the selection of articles in this review is shown in Fig. 1.

Fig. 2(a) shows the year-wise distribution of selected 39 studies. It is found that most of the studies are published between 2016 and 2019, with 25 studies accounting for 64% of the total. Between 2011 and 2015, a total of 8 articles (21%) are published. Only 15% of the total articles are published

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

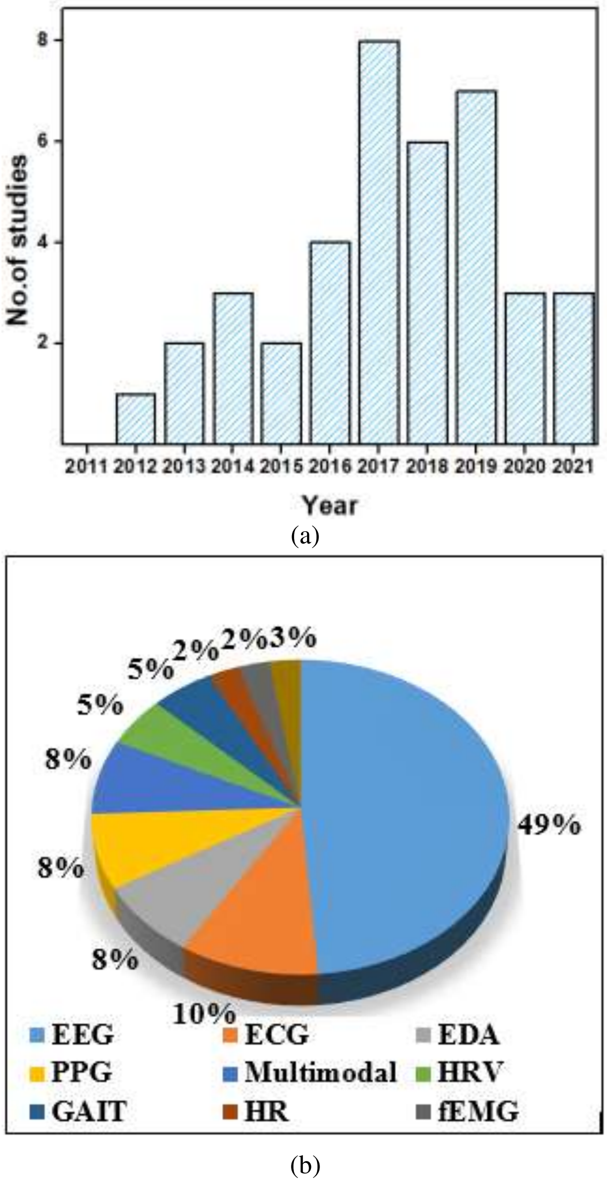

FIGURE 2. Distribution of selected 39 articles (a) year wise from 2011-2021 and (b) based on the signal modality used by the researchers

between 2020 and 2021. Fig. 2(b) shows the type of physiological signal used in the selected studies. It is seen that 49% of the 39 selected articles have been used EEG signals, followed by ECG signals (10%). The percentage of studies that used the EDA, PPG, and multimodal signals are 8%, while the GAIT and HRV signals are 5% each. HR and fEMG signals usage account for 2% each. The percentage of studies that used PPG signals is 3%.

B. SUBJECT INFORMATION

Among the reviewed articles, the number of participants varies depending on the type and field of the experiment. Several studies have shown that age, sex, and personality influence emotional states [93]. The age of participants in the majority of the selected studies is between 20 - 25 years old. It is found

TABLE I
DESCRIPTION OF THE CHARACTERISTICS OF EMOTIONAL STIMULUS

Characteristics	Description
EV	It refers to how close an emotional response in daily life is to actual emotional experiences
TR	It intimates the time taken to process emotional stimuli — higher the TR, the quicker the stimulation process, and vice versa.
CNT	It shows how easy or hard it is to control stimuli in experimental settings.
CMP	It represents how complex an emotional stimulation type may be. High complexity refers to many aspects of stimuli and vice versa.
EI	It expresses the strength of the emotional reaction that the stimulus will evoke.

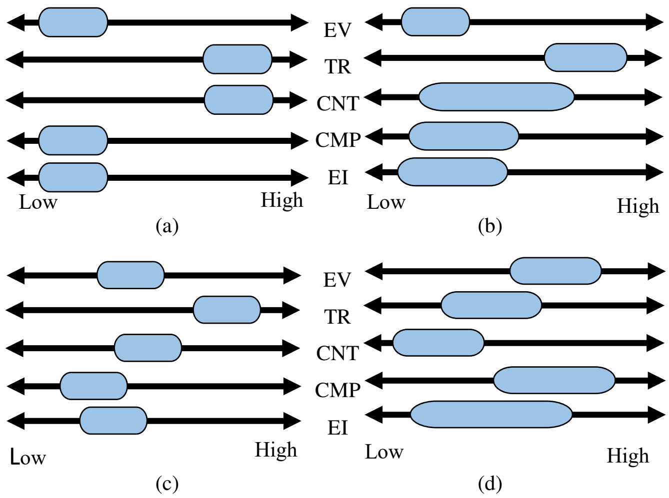

FIGURE 3. Emotional matrix for various stimuli using (a) words (b) images (c) faces, and (d) film clips [49].

that the participants are excluded based on the history of current or prior medicines [55], [91], information about psychiatric illnesses [39], [42], [55], [60], [61], [63], [67], [69], [91], [91], use of drugs or alcohol [42], [60], [61], [63], [67], [87], [91], perform any vigorous exercise before the experiment [67], difficulties in vision or hearing [55], [58], [67], [69], [87], [89], diabetes [70], and history of cardiovascular disease [41], [60], [70] which may delay the emotional responses. Eysenck personality questionnaire test have been used to select the healthy subjects [66].

In few studies, the authors have disclosed participants information, such as whether they are voluntary and/or provided a reward for participation [57], [58], [67], [68], [80], [91].

C. STIMULATION MODALITIES

The choice of emotional stimuli depends on the research question and can be easily determined using the stimuli emotion matrix [51]. Emotion matrix is a graphical representation of five critical emotional stimulus characteristics (see Fig. 3), namely, Ecological Validity (EV), Temporal Resolution (TR), Controllability (CNT),

TABLE II
THE EXPERIMENT PROTOCOLS USED IN THE SELECTED ARTICLES IN RECORDING VARIOUS MODALITIES USING AUDIO-VISUAL STIMULI

SR_id	Related work	Data collection method	No. of participants	Age (Mean ± std)	No. of stimuli	Length of stimuli (min)	Length of experiment (min)	Recorded modality	Sampling rate (Hz)	Affect experience measure	No. of annotators
SR01	[39]	Experiment	41	24.70 ± 4.70	10	2	~20	fEMG	2000	Discrete	4
SR02	[42]		53	24.00 ± 1.00	2	7	19	PPG	1000		--
SR03	[55]		8	24.00 ± 2.10	2	10	~20	EEG	250		--
SR04	[56]		8	23.00 ± 2.00	4	0.5	7	EEG	250		--
SR05	[57]		5	25.60 ± 2.40	2	4	15	PPG,SKT	200		--
SR06	[58]		5	23.18 ± 4.87	16	~ 1	20	GAIT	25		5
SR07	[59]		18	23.18 ± 4.87	16	~ 1	20	GAIT	25		5
SR08	[60]		48	23.50 ± 1.20	2	~ 7	29	ECG	1000		--
SR09	[61]		50	23.5	30	0.8 - 3	25	HR	25		--
SR10	[62]		28	--	3	~ 5	45	EEG	128		--
SR11	[63]		20	22.00 ± 2.00	2	10	36	PPG, Facial expressions	800		--
SR12	[64]		60	23.00 ± 2.00	3	--	--	ECG	1000		--
SR13	[65]		16	22.50 ± 1.80	9	2	36	EEG	1000		--
SR14	[66]		300	--	2	4.5	~13	ECG, Facial expressions	--		--
SR15	[67]		10	22.00 ± 2.10	2	30 and 40	96	EDA	26	Continuous	--
SR16	[68]		24	20.86 ± 2.77	48	5 - 6	45	EDA	1000	Discrete	--
SR17	[69]		10	22.25 ± 1.09	30	0.5	~48	EEG	128	Continuous	10
SR18	[70]		12	28.00 ± 6.20	2	6 and 12	30	EEG	256	Discrete	--
SR19	[71]		16	22.50 ± 1.80	--	--	--	EEG	--		--
SR20	[72]		20	22.50 ± 1.80	12	2.5	~31	EEG	256		60
SR21	[73]	Database (DEAP)	32	26.90	40	1	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512	Continuous	14
SR22	[74]	Experiment	37	35.00	4	2 - 4	~23	EEG	500	Discrete	--
SR23	[75]	Database (MAHNOB)	30	26.06 ± 4.39	20	0.58 - 1.95	50	ECG, EEG, RDP, SKT	1024	Continuous	50
SR24	[76]	Database (DEAP)	32	26.90	40	1	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512		14
SR25	[77]	Experiment	2	22.00	2	10	~20	EEG	--	Discrete	--
SR26	[78]		33	27.00	2	1.25	~3	PPG, Facial expression	60		494
SR27	[79]		5	23.00	8	5	24	RSP, Facial expression	--		--
SR28	[80]		112	51.64 ± 6.60	3	1.2	~15	fEMG, HRV, EDA	1000		31
SR29	[81]	Database (LUMED-2)	11	--	--	1-2.5	16	EEG, EDA, HR, Temperature	500		--
		Database (DEAP)	32	26.90	40	1	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512	Continuous	14
SR30	[82]	Database (DECAF)	30	27.30 ± 4.30	36	1	60	MEG, ECG, EOG, EMG	1000		42
SR31	[83]	Database (DEAP)	32	26.90	40	1	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512		14
SR32	[84]	Experiment	4	--	3	2.5	~10	ECG, EDA	250	Discrete	--
SR33	[85]	Database (DEAP)	32	26.90	40	1	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512	Continuous	14
SR34	[86]	Database (SEED)	15	23.30 ± 2.40	24	~2	~68	EEG, Eye movements	1000	Discrete	45
SR35	[87]	Experiment	55	36.50 ± 10.9	8	1 - 2	~12	EEG	512		--
		Database (DEAP)	32	26.9	40	~2	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512	Continuous	14
		Database (SEED)	15	23.30 ± 2.40	24	1	~68	EEG, Eye movements	1000	Discrete	45
SR36	[88]	Database (SEED)	15	23.30 ± 2.40	24	~2	~68	EEG, Eye movements	1000		45
SR37	[89]	Database (DEAP)	32	26.9	40	~2	~47	EEG, EDA, BP, RSP, SKT, EMG, EOG	512	Continuous	14
		Database (SEED)	15	23.30 ± 2.40	24	1	~68	EEG, Eye movements	1000	Discrete	45
SR38	[90]	Experiment	46	--	--	--	--	ECG	--	Continuous	--
SR39	[91]		40	21.63 ± 1.51	6	0.5 - 5	~45	EEG, EOG	500		--

Complexity (CMP), and Emotional Intensity (EI) which allows researchers to select suitable stimuli in affective computing (see Table I). The emotional stimulus must-have characteristics such as low CMP, low CNT, high EI, high TR, and high EV to elicit strong emotional reactions [51].

Compared to the text, audio and images, the audio-visual stimuli have desirable properties, namely high EV and being dynamic for emotional elicitation. Based on the effectiveness of audio-visual stimulus to induce emotions, the articles using only audio-visual stimuli for eliciting the dichotomous emotional states are considered and represented in Table II. The references of the selected 39 studies are assigned with a Systematic Review_id (SR_id) as shown in Table II for convenience of accessibility in the rest of the manuscript.

In the selected studies, emotions are elicited using video clips. The audio-visual clips are usually taken from publicly available databases, such as a standardized database of Chinese emotional film clips (SR39), China's standard emotional video stimuli materials library (SR09), and the affective body movement library of ballet movements (SR16). In some studies, video clips are collected from various commercial movies (SR10, SR15, SR18, SR25, SR26), and internet sources (SR19). In 11 of the studies, the physiological signals are directly considered from online public databases such as DEAP (SR21, SR24, SR29, SR31, SR33, SR35, SR37), lumed-2 (SR29), DECAF (SR30), SEED (SR34, SR35, SR36, SR37), and MAHNOB-HCI (SR23).

Few of the works have not mentioned about source of stimuli used for emotion elicitation. Interestingly, the number and length of the stimuli are not the same and vary for different published articles. Table II shows that the minimum number of video clips used is two, and the maximum number of video clips used is a hundred. Also, the least duration of stimulus used is 0.5 min (SR04, SR17, SR39), and the maximum duration is 40 min (SR15). In 20 of the studies, film clips have been selected with the help of annotators.

D. DATA ACQUISITION PROTOCOL USING AUDIO-VISUAL STIMULI

The protocol followed in the selected articles is summarized in the flowchart shown in Fig. 4. From Table II it is observed that hat the least duration of the experiment is approximately three min (SR15) and the maximum duration is 96 min (SR26). Before starting the experiment, the procedure has been explained clearly to the subjects, and the consent form is filled. The experiment is carried out in a 30 dB soundproof room (SR09, SR10, SR35) with well-lit (SR03) and constant temperature (24 ± 2°C) (SR08) or in a laboratory environment (SR14), where exact measurements are obtained.

To avoid mind wandering, the subject has to be brought into the neutral states using different methods such as taking rest (SR02, SR09, SR11, SR12, SR18), closing eyes for 60 seconds (SR22), performing GO/NO-GO task (SR39), and watching a neutral video (SR09 – SR11).

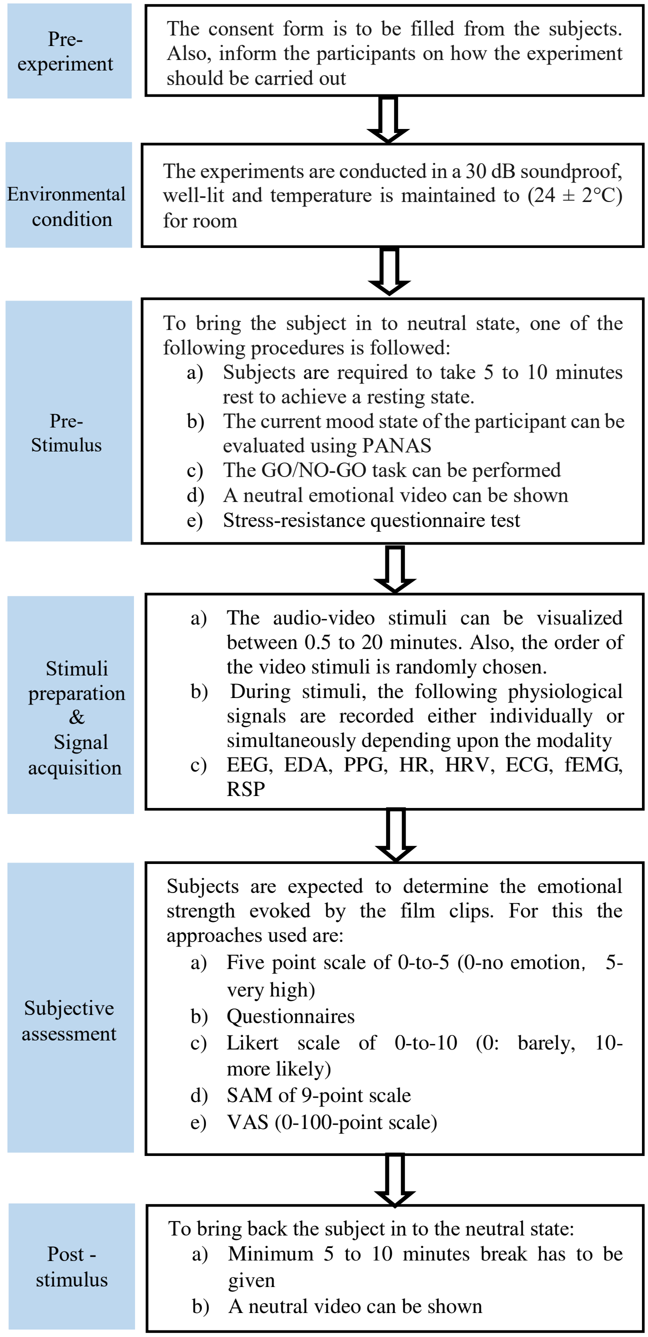

FIGURE 4. Flowchart of data acquisition protocol using audio-visual stimuli.

Before watching stimuli, the mood of the participant is identified by various methods such as rating the subject mood on the Positive and Negative Affect Schedule (PANAS) scale (SR06, SR07), from the self-report questionnaire (SR18) and by conducting a stress-resistance questionnaire test (SR15). During the experiment, the videos are displayed randomly. However, there is no influence of random videos on emotion responses (SR02, SR06 – SR09, SR11 – SR13). Participants are also instructed to wear a headset while watching stimuli to avoid unwanted ambient sound and prevent physiological signals affected by the conversation between subjects (SR15).

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

The single (unimodal) or multiple (multimodal) physiological signals are acquired at various sampling rates ranging from 25 to 2000Hz. Four of the selected studies have used a multimodal approach. Park et al. classified happy and sad emotions by fusing two peripheral signals such as PPG and skin temperature (SR05). A hybrid fusion strategy has been employed using facial expressions, EDA, and EEG signals to classify happy, sad, and neutral emotions (SR29). Two multimodal fusion methods between ECG and EDA signals are used for happy or sad emotional state recognition with reference to a neutral state (SR32). Steenhaut et al. assessed fEMG, EDA, and ECG signals to measure the emotional reactivity of subjects during happy and sad emotions (SR28).

1) VALIDATION OF PHYSIOLOGICAL SIGNALS

The emotions felt by the subjects are validated with self-reports using various methods such as Self-Assessment Manikin (SAM), Visual Analogical Scale (VAS), Likert scale, questionnaire, and press file (SR01, SR04, SR06, SR07, SR10, SR13, SR14, SR16, SR17, SR18, SR20, SR26 – SR28, SR32, SR35, SR39). In one of the selected studies, happy and sad emotions are labeled from the valence ratings that are obtained using SAM. The video is labeled as sad when the valence rating is ≤ three and happy when the valence rating is ≥ seven (SR17). Krishna et al. have also considered SAM as ground truth for assessing the happy, sad, relax and fear emotional states of the subject (SR20).

Christensen et al. used VAS scale ranging from 0 to 100 ('0' – 'sad', '50' – 'neutral', and '100' – 'happy') for measuring behavioral or subjective experience. The range of the scale is selected using a mouse cursor present on the screen (SR16). Steenhaut et al. also used the VAS scale to indicate subjective emotional reactivity (SR28). The lower end of the VAS scale indicates neutral and the higher end as happy or sad (SR28). In another study of fEMG based emotion recognition, the happy and sad emotion felt by the subject are rated using the VAS scale (SR01).

After watching audio-visual stimuli, the subjective tendency of emotions is collected from the questionnaire to validate happy and sad labels. The questionnaire includes the level of emotion felt by the subject, tendency of emotion for a given audio-visual stimulus (SR18). Das et al. have used a questionnaire to indicate the intensity of happy and sad emotion felt by the subject on a range from 0 to 10. The videos with an intensity level > seven are only considered for further analysis (SR32). Rakshit et al. have used an online questionnaire to determine the familiarity of the happy and sad video on a scale of 0 to 4 ('0' – 'no emotion', '4' – 'maximum emotion') (SR26). The data belongs to no emotion felt by the subject is discarded for further analysis (SR26). Questionnaires, namely type and intensity of emotion elicited by happy, sad, and calm, are considered to validate affect (SR13).

Gao et al. have used a feedback form for validating the emotions triggered by joy and sadness videos (SR27). A self-assessment form has been used to label the positive emotion induced by happy video and negative emotion induced by sad (SR04). Singhal et al. have used a web-based online form to validate happy, sad, and neutral emotions by collecting participant ratings on a scale of 1-5 ('1' – 'very poor' and '5' – 'very good') (SR10). Likert scale ranging from 0-10 has been used for obtaining intensity of happy and sad emotions felt by the subject (SR06, SR07). Liu et al. uses press file to represent two strings, namely '0' (target emotion is perceived) and '1' (target emotion is not perceived) to obtain participants subjective experiences for happy, sad, fear, and anger emotional states (SR14).

SAM (SR39) and self-assessment form (SR35) have also been used to obtain the ground truth labels for differentiating positive and negative emotional states. Six of the selected studies used high definition cameras to record participant's facial expressions during the experiment (SR11, SR14, SR26, SR27, SR29, SR35). Only six studies have reported the details of an ethical committee approval and the validation of the protocol before experimenting (SR01, SR02, SR08, SR09, SR39). Also, one of the selected studies mentioned that the experimental protocol have been implemented in strict accordance with the declaration of Helsinki (SR15).

E. INSTRUMENTATION APPROACHES TO DIFFERENTIATE DICHOTOMOUS EMOTIONAL STATES

During stimuli visualization, various instruments are used to acquire physiological signals. In order to understand the performance based on instrument characteristics, it is important to consider some of the common factors associated with the hardware specifications. The design of instruments is affected by factors such as user, technology, medical, environmental, and economic-related factors (see Fig. 5) [94], [95].

1) USER RELATED FACTORS

When dealing with user-related factors, the instrument should take less time duration to set up device and subject preparation [95]. The instrument must be easy to wear by the subject without limiting normal activity and causing additional distress [96]. The instrument with good usability can bring a positive experience to the subject [97]. The portable instruments open a new path to the non-intrusive field of assessment of emotions [98]. For example, Emotive devices are portable and are comfortable to use in comparison to Neuroscan devices. Also, the setup time of Neuroscan devices is high compared to the Emotive devices [99].

2) MEDICAL RELATED FACTORS

The electrical safety of the medical equipment is the most important, and only devices tested for safety should be used in hospitals [95]. The parameters, namely comfort level and system usability, are crucial in the instrument for biofeedback acquisition. The non-invasive instruments are comfortable and easier to use for both the therapist and patient [96]. In long-term tracking applications, systems without direct skin contact provide many advantages, such as reliability and electrical

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

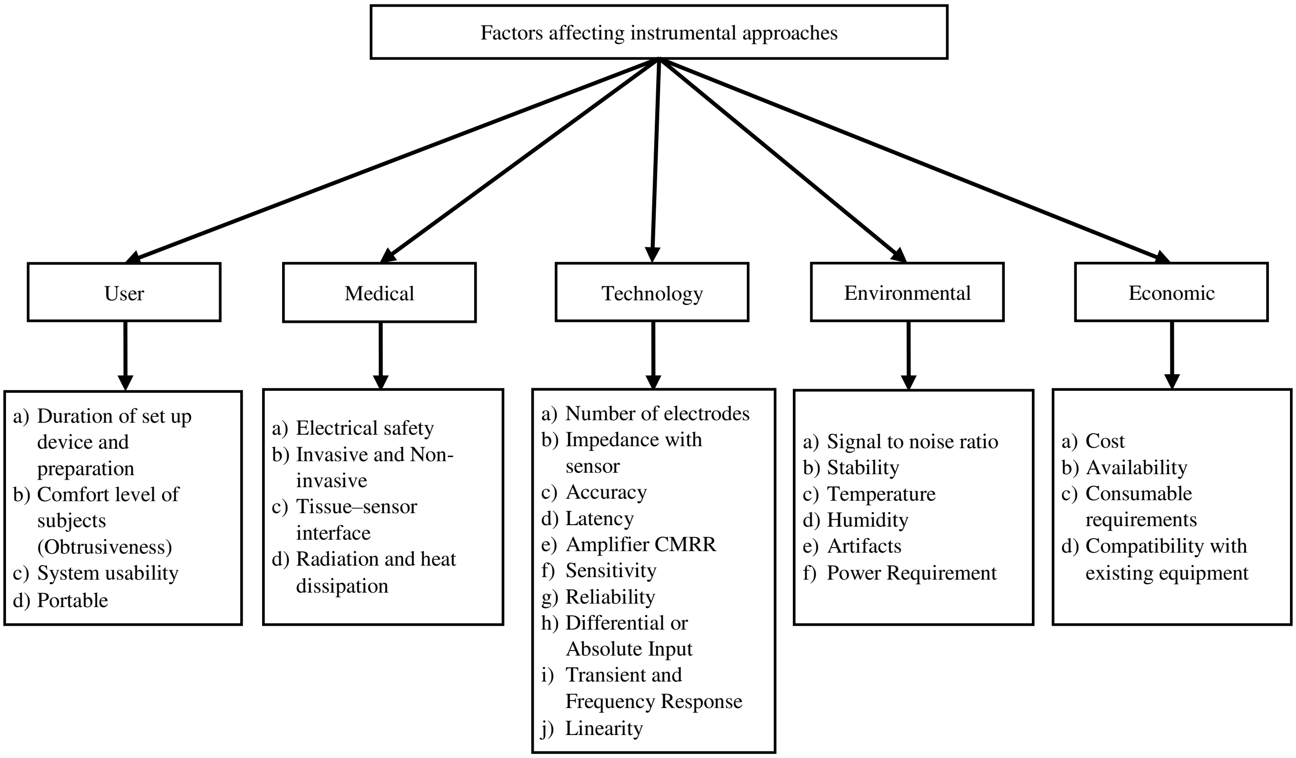

FIGURE 5. Various factors affecting on instrumentational approaches.

isolation with the sensor surface [100]. The instruments should dissipate nominal heat. The excess heat and radiation generated by the instrument may cause irreversible changes in the tissue [95].

3) TECHNOLOGY RELATED FACTORS

The multi-electrodes devices are expensive and may be uncomfortable in real-life situations. In most devices, the input impedance, linearity, sensitivity, and Common Mode Rejection Ratio (CMRR) are made high, and latency of the device is driven low for an accurate measurement. The accuracy of emotion recognition also varies between instrument and derivatives, the placement of electrodes. High CMRR refuses all unwanted signals in the_preamplifier stage, so only the desired signals find a way into the amplifier [94]. Reliable instruments can have standards that allow physicians or clinicians to decide if their patients are normal or abnormal. The instruments with differential input can operate at lower voltages while maintaining high SNR [94], [95].

4) ENVIRONMENTAL RELATED FACTORS

Increasing Signal to Noise Ratio (SNR) can reduce the effect of environmental noise in biomedical instrumentation systems. The stable instrument ensures that results are repeatable and reproducible [95]. The medical devices have to function appropriately in the suggested values for temperature and air humidity. Also, they must be less prone to movement artifacts and designed for minimum energy consumption [95].

5) ECONOMIC RELATED FACTORS

The cost of the instrument and its maintenance, such as labor and spare parts, must be inexpensive. The availability of trained manpower, availability of consumables, and compatibility with existing equipment is always challenging.

F. COMPARISON OF INSTRUMENTS USED FOR MEASURING DICHOTOMOUS EMOTIONAL STATES

The comparison of key parameters and characteristics related to the instruments used in the selected studies is summarized in Table III. The instruments such as Super Spec EEG (SR03), Neuroscan (SR13, SR34, SR36, SR37, SR39), Neurowin (SR04), EEG traveler (SR20), Biosemi ActiveTwo (SR21, SR23, SR24, SR 31, SR33), Enobio (SR22, SR29), Neurosky mindwave (SR35), and, Emotive EPOC (SR10, SR17, SR18) have been used for monitoring brain activities. Among the available instruments, the NeuroSky (SR35) and Emotiv system (SR10, SR17, SR18) is found to be a good option in terms of the number of channels, setup time, intrusiveness, size, cost, and compatibility. However, it is limited by low input impedance.

The instruments, namely Bioneuro multi-channel feedback (SR15), Biopac (SR28), EMPATICA E4 (SR29), and Power lab (SR 16) have been used for acquiring EDA signals. Among these instruments, the wearable device EMPATICA E4 Wristband (SR29) can be preferred because of its setup time, cost, real-time usage, portability, and the number of channels used. Further, it is found that Biopac (SR28) and Power Lab (SR16) have similar specifications in all aspects (from Table III).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

TABLE III
KEY PARAMETERS AND CHARACTERISTICS RELATED TO INSTRUMENTS SPECIFICALLY USED FOR MEASURING DICHOTOMOUS EMOTIONAL STATES

Instrument	SR_id	Setup time	Comfort level	Port-able	Non-Invasive	Cost	Comp atible	Input range	Input impedance	Sensit ivity	SNR	Safe -ty
Super Spec EEG, 32-channel	SR03	~	~	~	√+	~	--	~	√	√	√	--
Neuroscan equipment, 64-channel	SR13, SR34, SR 35, SR36, SR37, SR39	~	~	~	√+	~	√+	√	√+	√	√	--
NEUROWIN, 19 channel	SR04	~	~	~	√+	~	--	--	--	--	--	--
Emotive EPOC + headset, 14 channel	SR10, SR17, SR18	√+	√	√+	√+	√+	√+	~	~	√	√	√+
BioNeuro multichannel biofeedback instrument	SR15	√	√	√	√+	√	--	~	√+	√+	√+	√+
EEG traveler 24CH	SR20	~	√	√	√+	√	--	~	~	√+	√	√+
Biosemi ActiveTwo system	SR21, SR23, SR24, SR29, SR31, SR33, SR35, SR37	~	~	√	√+	~	√	√	√	√+	√	√+
Enobio device	SR22, SR29	~	√	√	√+	√	√+	√	√+	√	√+	√+
NeuroSky MindWave Mobile 2 headset	SR35	√+	√+	√+	√+	√+	--	--	--	--	--	--
Biopac- MP150	SR14, SR28	√	√	√	√+	~	√+	√+	~	√	√	√+
Multi-channel electrophysiological recording system - RM6240	SR02, SR08, SR11, SR12	√	√	√	√+	~	--	√	√+	√+	√+	√+
Samsung Gear 2	SR06, SR07	√+	√+	√+	√+	√+	√+	--	--	--	--	√+
EMPATICA E4 wristband	SR29	√+	√+	√+	√+	√+	√+	--	--	--	--	√+
TSD200A and TSD 200D sensors with Biopac	SR05	√+	√	√	√+	~	√+	√+	~	√	√	√+
Pulse oximeter	SR26	√+	√+	√+	√+	√+	√+	--	--	--	--	√+
Algoband F8	SR09	√+	√+	√+	√+	√+	--	--	--	--	--	--
Digital-IF Doppler radar	SR27	√+	√+	√	√+	√	--	--	--	--	--	√+
Power Lab data acquisition device	SR01, SR16	√	√	√	√+	~	√+	√+	~	--	--	√+
Insufficient information	SR19, SR25, SR30, SR32, SR38											

√+ = Good, √ = Moderate, ~ = Poor, -- = Data not available.

However, in the laboratory environment, Biopac (SR28) or Power Lab (SR16), or BioNeuro multi-channel feedback (SR15) is also a good choice because of its high input impedance, sensitivity, and SNR. BioNeuro multi-channel feedback (SR15) has a very high input impedance compared to the power lab (SR16) and Biopac (SR28). However, the input range of Biopac (SR28) and Power lab (SR16) is higher when compared to BioNeuro instruments (SR15).

ECG signals are acquired using Biopac (SR28) and Multi-channel electrophysiological recording system (RM6240) (SR08, SR12, SR18). The RM6240 has advantages such as high input impedance, sensitivity, and SNR compared to Biopac (SR14, SR28).

Samsung Gear 2 smartwatch (SR06, SR07) is used for collecting GAIT data. This wearable device may have several advantages, such as minimal electrodes, less setup time, unobtrusive, portable, and less cost. For PPG signal acquisition, the instruments, namely Algoband F8 (SR09), Pulse oximeter (SR26), TDA sensor (SR05), and RM6240 (SR02, SR11) have been used. Algoband F8 (SR09) or Pulse oximeter (SR26) can be used among these instruments in terms of portability, setup time, device usage, and cost.

Power Lab (SR01) and Biopac (SR28) have been used for fEMG signal recording. Since both of these devices have similar specifications, any of these instruments can be preferred. Digital-IF Doppler radar (SR27) has been used for measuring respiratory signals. This device has advantages such as less setup time, non-contact type, and more comfortable to the participant.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

TABLE IV
COMPARISON OF VARIOUS MEASUREMENT METHODS IN DIFFERENTIATING DICHOTOMOUS EMOTIONAL STATES USING AUDIO-VISUAL STIMULI

	Instrument	Advantages	Disadvantages
EEG	Super Spec EEG, 32-channel (SR03) Neuroscan equipment, 64-channel (SR13, SR34, SR35, SR36, SR 37, SR39) NEUROWIN, 19 channel EEG Equipment (SR04) Emotive EPOC + headset, 14 channel (SR10, SR17, SR18) EEG traveler 24CH (SR20) Biosemi ActiveTwo system (SR21, SR23, SR24, S29, SR31, SR 33, SR35, SR37) Enobio device (SR22, SR29) NeuroSky MindWave Mobile 2 headset (SR35)	• Fast and reliable • High time and frequency resolution • Directly reflects the neural activity of the emotions and monitors cognitive-affective processing in the absence of behavioral responses.	• Complex installation, high maintenance • Low spatial resolution with poor signal-to-noise ratio, Poor estimation of neuronal activity below the cortex • Lack of Model generalizability for tackling individual differences.
EDA	BioNeuro multichannel biofeedback instrument (SR15) Biopac- MP150 (SR28) EMPATICA E4 Wristband (SR29) Power Lab data acquisition device (SR16)	• One of the best real-time correlates of emotions • Simple, non-obtrusive, easily recordable, low cost, and easy to install • Phasic response of EDA is generally discriminable	• Limited runtime in real-time measurements • Influence of external factors such as temperature and humidity • EDA responses are delayed by 1-3s with respect to sympathetic activity and intra and inter-subject variability
ECG	Biopac- MP150 (SR14, SR28) Multi-channel electrophysiological recording system - RM6240 (SR08, SR18, SR12)	• Portable, reliable, non-intrusive and computationally efficient • Mobile measurements (i.e., smart clothing, smartwatch) • High amplitude compared to other methods	• It is established as a biometric characteristic. Therefore, it intrinsically has high inter-subject variability • Higher accuracy in stationary measurements • Movement artifacts in mobile systems
GAIT	Samsung Gear 2 (SR06, SR07)	• Non-invasive • Cooperation or attention of a person is not needed, and the gait may be distantly interpreted. • Strong ecological validity	• High inter-subject variability, Still in its infancy, may not be adequate • Strongly depends on the control over clothing and footwear • Calibration of accelerometers and motion artifacts
PPG	TSD200A and TSD 200D sensors (Biopac, USA) (SR05) Smart bracelet sensor -Algoband F8 (SR09) RM6240C multi-channel signal acquirement system (SR11) RM6240B system (SR02) Pulse oximeter (SR26)	• Simple to implement on wearable consumer electronics • Non-invasive, • Easy and convenient blood volume change, HR and O_2 concentration can be measured at the same time	• Inaccuracy in tracking the PPG signals during daily routine activities due to motion artifacts caused by hand movements
fEMG	Power Lab data acquisition device (SR01) Biopac 150 (SR28)	• Applicability of real-time scenario	• Prone to noise generated by muscle activity • Measure only valence and complicated installation • Amplitude vary on chosen measurement location
RSP	Digital-IF Doppler radar (2.4GHz, -7dBm transmit-ting power) (SR27)	• Non-contact monitoring • Improved accuracy • Suitable for long term monitoring	• Motion artefact

Four of the selected articles have not mentioned the instrument type or model used for recording physiological signals (SR19, SR25, SR30, SR32, SR38).

G. COMPARISON OF MEASUREMENT METHODS USED FOR HAPPY AND SAD EMOTIONAL STATES

During stimuli visualization, various physiological and non-physiological traits are acquired from the corresponding instrumentation approaches. The comparison of measurement methods in differentiating dichotomous emotional states using audio-visual stimuli is summarized in Table IV. The physiological measurement methods such as EEG, fEMG, EDA, ECG, PPG, RSP, and a non-physiological measurement method, GAIT, have been used to classify happy and sad emotional states selected review articles. The physiological signal, EEG, directly reflects the neural activity of the emotions, but the installation and maintenance cost of these devices is very high [101].

The EDA measurements are simple and are easy to install [102] but are influenced by external factors such as temperature and humidity [102], [103]. ECG generates a higher magnitude output signal compared to other methods. However, these measurements have limitations such as high inter-subject variability and low accuracy due to movement artifacts in mobile systems. Although PPG provides physiological variations, inaccuracy in tracking the PPG signals during daily routine activities due to motion artifacts caused by hand movements is one of the main limitations [104]. EMG has limitations such as susceptible to noise, measures only valence, and difficult to set up. Although this method has a good spatial resolution, it is limited by cost and time resolution. The non-physiological method, the GAIT pattern has strong ecological validity; they are still in their infancy.

H. FEATURE EXTRACTION

For the classification of happy and sad emotional states, the time, frequency, and Time-Frequency (TF) domain features were used.

1) TIME-DOMAIN FEATURES EXTRACTION

In the EEG context, features such as, mean (M), median (Med), standard deviation (Std), correlation, average energy (Eng), root mean square (RMS), number of peaks, average power (Pow), the first-order difference (1st diff), the second-order difference (2nd diff), kurtosis (Ku), variance (Vr), skewness (Sk), entropy (En), complexity (CO), mobility (MO), and auto regressive parameter are extracted (SR03, SR10, SR18, SR19, SR22, SR25). For EDA, features, such as maximum (Max), minimum (Min), dynamic range, Ku, Sk, M, Vr, mode, and M of 1st diff are computed (SR15, SR32). Detrended fluctuation analysis, permutation patterns entropy (PPE), and ordinal pattern entropy (OPE) have been estimated from the preprocessed ECG signal (SR12, SR14).

In HRV, the features such as the square root (SQRT) of the mean squared differences, M, STD, non-linear indices, PPE, and OPE have been extracted (SR08, SR12). From the PPG signal, the features such as M, Med, Std, reflection index (RI), and stiffness index are evaluated (SR02, SR05, SR11, SR26). The features, namely M, Std, and 2nd diff are extracted from RSP signal (SR27).

Along with time-domain features, Li et al. also computed morphological features (SR02). Minio-Paluello et al. used analyses of variance (ANOVA) for the classification of dichotomous emotional states (SR01). In one of the studies, non-linear analysis such as the correlation dimension (CD) of hemispheres was compared as a complexity measure of the EEG signals (SR23).

2) FREQUENCY DOMAIN FEATURES EXTRACTION

Features, namely squared coherence estimate, Vr, MO, CO, frequency cepstral coefficient, spectral Shannon, and k-NN entropy, are calculated from EEG signal (SR19, SR21, SR31, SR 35). Lee and Hsieh extracted brain functional connectivity pattern-based features, namely coherence, phase synchronization index (SR39). Welch's power spectral density has been computed from EDA signals (SR32). From the HRV signal, the power spectral density (PSD) is computed at Low Frequency (LF) and High Frequency (HF), and LF to HF power ratio (SR08). The indices of LF power, HF power, and LF to HF power ratio in the power spectral density are calculated from PPG signal (SR11, SR26). The E of PSD at different frequencies is extracted from RSP (SR27).

3) TF DOMAIN FEATURES EXTRACTION

The feature extraction of EEG signals in the TF domain is carried out by decomposing the useful sub-bands by one of the following methods: Short-time Fourier Transform (STFT), Dual-Tree Complex Wavelet Transform (DTCWT), Discrete Wavelet Transform (DWT), and Tunable Q Wavelet Transform (TQWT) (SR13, SR17, SR19, S20, SR21, SR22, SR24, SR33, SR34).

TABLE V
THE SUMMARY OF THE FEATURES USED IN THE INSTRUMENTATION APPROACH

Signal	Related work	Features		
		Time	Frequency	TF
EEG	SR03, SR04, SR10, SR13, SR17–SR25, SR31, SR33 – SR 37, SR39	16	9	27
EDA	SR15, SR16, SR28, SR29, SR32	9	1	--
ECG	SR12, SR14, SR30, SR38	8	--	11
GAIT	SR06, SR07	17	-	-
HR	SR09	6	-	-
HRV	SR08, SR12, SR28	8	3	-
RSP	SR27	6	5	-
fEMG	SR01, SR28	3	--	--
PPG	SR02, SR05, SR11, SR26	15	12	-

The features, namely Eng, instantaneous phase, and absolute power, are computed from certain bands of EEG signal by applying DTCWT to the selected channels (SR13). The absolute Max, absolute M, Std, Pow, Eng, En, differential En, Vr, MO, and CO features have been computed from the wavelet coefficients of each sub-band generated by using the DWT method (SR19, SR21, SR22, SR24, SR33).

By using the TQWT decomposition method, the features such as mean absolute value, Pow, Std, Sk, and Ku have been computed from each sub-band of EEG signal (SR34). Similarly, Krishna et al. have calculated the time-domain features (RMS, absolute sum and SQRT sum, change in average amplitude, log detector, clearance factor, shape factor, and crest factor) from the amplitude at sampling points of each sub-band, and Hjorth features (Vr, MO, and CO) from the Std of each sub-band (SR20). Gao et al. fused power spectrum generated from STFT and wavelet energy entropy computed from DWT that are derived from the different frequency bands of EEG signal (SR17).

Considering the ECG signal, basic statistical features (M, Std, Min, and Max) are extracted from the DWT coefficients at level 4 decomposition. Similarly, total power, LF, HF, and LF to HF power ratio features have also been computed from the intrinsic mode functions generated by the DWTs empirical mode decomposition and wavelet coefficients at level 14 decomposition (SR30).

According to the survey, it is found that the time domain features are mostly used in all instrumentation approaches, followed by frequency domain and TF features. The summary of all the features in the respective instrumentation approach is given in Table V.

TABLE VI
THE SUMMARY OF CLASSIFIERS AND RESPECTIVE PERFORMANCE METRICS OBTAINED TO CLASSIFY DICHOTOMOUS EMOTIONS

Signal	Classification type	Sessions recorded	SR_id	Feature selection algorithm	Classifier	Target emotions	Classifier performance			
							Average accuracy (%)	F-score (%)	TPR	FPR
EEG	SD	SS	SR03	--	LDA	R	92.70	--	--	--
						H	84.37	--	--	--
						S	78.12	--	--	--
			SR10	--	RF	H-S-Nu	83.93	--	--	--
			SR17	Principal component analysis	SVM		89.17	--	--	--
					RVM		91.18	--	--	--
			SR18	--	NB	H-S	87.50	--	--	--
			SR22	--	ANN	H	63.63	--	--	--
						S	100	--	--	--
		MS	SR04	--	LDA and SVM	N	87.35	--	--	--
						H	84.82	--	--	--
						S	86.43	--	--	--
	SI	SS	SR13	--	SVM	H-S-C	90.61	--	--	--
			SR19	--	SVM	H-S	96.81	--	--	--
			SR20	--	ELM		87.10	--	--	--
			SR21	Particle swarm optimization	SVM	H	74.19	--	--	--
						S	69.44	--	--	--
			SR24	Sequential minimal optimization	SVM	H	72.73	--	--	--
						S	88.89	--	--	--
			SR33	--	MLPNN	P-N	77.14	--	--	--
					kNN		72.92	--	--	--
			SR35 (DEAP)	--	eDGP		84.81	--	--	--
			SR39	Analyses of variance	QDA		82.00	--	--	--
			SR37 (DEAP)	Minimal redundancy maximal relevance	ELM		69.67	--	--	--
		MS	SR37 (SEED)	Minimal redundancy maximal relevance	ELM	P-N	91.07	--	--	--
			SR34	--	RoF with SVM		93.10	--	--	--
					RoF with kNN		88.80	--	--	--
					RoF with ANN		91.50	--	--	--
					RoF with RF		90.60	--	--	--
					RoF with CART		88.50	--	--	--
					RoF with C4.5		88.50	--	--	--
					RoF with REP Tree		86.90	--	--	--
					RoF with LAD Tree		86.60	--	--	--
			SR35 (Experiment)	--	eDGP		86.55	90.42	--	--
			SR35 (SEED)	--	eDGP		86.22	--	--	--
			SR36	--	ARF		94.40	--	0.963	0.948
EDA	SI	SS	SR15	Particle swarm optimization	kNN	H	65.38	--	--	--
						S	87.50	--	--	--
ECG	SD	MS	SR30	--	kNN	H-S	75.00	--	--	--
	SI	SS	SR31	--	kNN	H-S	75.00	--	--	--
			SR14	--	Fisher	H	--	--	0.8956	0.0058
						S	--	--	0.9010	0.0162
			SR38	--	RF	P	92.10	92.60	--	--
						N	93.90	90.70	--	--
		MS	SR30	--	kNN	H-S	65.00	--	--	--

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

TABLE VI (CONTINUED.)
THE SUMMARY OF THE CLASSIFIERS AND THE RESPECTIVE PERFORMANCE METRICS OBTAINED TO CLASSIFY DICHOTOMOUS EMOTIONS STIMULI

GAIT	SD	SS	SR06	--	Baseline	H-S	~51.00	--	--	--
					RF		~69.00	--	--	--
					LR		~68.00	--	--	--
	SI	SS	SR07	--	Baseline	H-Nu-S	03.10	03.10	--	--
					RF		65.10	78.70	--	--
					LR		68.20	76.30	--	--
HR	SI	SS	SR09	SelectKBest	kNN	H-S	56.00 (k=20)	--	--	--
					RF		82.00 (k=10)	--	--	--
					DT		76.00 (k=5,8)	--	--	--
					GBDT		84.00 (k=8)	--	--	--
					AdaBoost		80.00 (k=5)	--	--	--
RSP	SI	SS	SR27	--	kNN	J-S	85.00	--	--	--
ECG+EDA	SI	SS	SR32	--	SVM	H-S	EDA:100 ECG: 97.27	--	--	--
					NB		EDA:100 ECG: 98.92	--	--	--
					kNN		EDA:100 ECG: 88.53	--	--	--
PPG+ SKT	SD	SS	SR05	--	SVM	H-S	SKT:89.29 PPG:63.66 SKT+PPG: 92.83	--	--	--
Face+ EEG+ EDA	SD	SS	SR29 (LUMED-2)	--	kNN	H-S	53.80	--	--	--
	SI	SS	SR29 (DEAP)	--	kNN	H-S	75.00	--	--	--

SD – Subject dependent, SI – Subject independent, SS – Single session, MS – Multiple sessions, H – Happy, J – Joy, S – Sad, Nu – Neutral, C – Calm, R – Relax, P – Positive emotion, N – Negative emotion

I. CLASSIFICATION AND STATISTICAL ANALYSIS

Classification and differentiation of dichotomous emotional states are carried out using several classifiers and statistical analysis methods. For this, features extracted from various signals using different instrumentation approaches are considered. Out of 39 articles, 30 articles have used classification algorithms, and nine articles have used statistical analysis methods.

1) CLASSIFICATION

Out of 30 classification articles, 23 articles classify happy and sad emotional states, and the remaining seven articles classify positive and negative emotional states. The summary of the classifiers and the respective performance metrics, namely accuracy, F-score, and True Positive Rate (TPR)/False Positive Rate (FPR), are listed in Table VI.

Out of 23 happy and sad classification articles, 11 articles have used EEG signals with machine learning algorithms, namely Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Random Forest (RF), Relevance Vector Machines (RVM), Naïve Bayes (NB), Extreme Learning Machine (ELM), and Artificial Neural Networks (ANN). The highest classification accuracy of 96.81% has been achieved using the SVM classifier and wavelet coefficient features. The EEG signals in the study are recorded in SS, and SI analysis has been carried out for classification (SR19). Another SI study on EEG signals acquired in MS have obtained the least accuracy of 63.63% in classifying happy emotional states using ANN (SR22). In the case of EDA signals, Srinivasan et al. have used SI analysis and achieved a classification accuracy of 65.38% and 87.50% for happy and sad emotional states, respectively, using the kNN algorithm (SR15).

The classifiers, namely k-Nearest Neighbors (kNN) and Fisher, have been used to categorize happy and sad emotions from ECG signals. The maximum accuracy of 75% for SI analysis has been achieved using the kNN algorithm (SR31). Cheng et al. reported the TPR/FPR metric of 0.8956/0.005 and 0.9010/0.0162 for happy and sad emotions, respectively, using the Fisher classifier and SI analysis (SR14). Another SI study conducted on ECG signals recorded in MS has achieved the least classification accuracy of 65% in classifying happy and sad emotional states using kNN (SR30). Quiroz et al. have performed both SD and SI analysis on GAIT pattern data using three classifiers: Baseline, RF, and Logistic Regression (LR). In both studies, the experiment is conducted in SS. The maximum accuracy of 68.20% (F-score: 0.7630) has been obtained for SI analysis using the LR algorithm (SR06, SR07). Recently, Shu et al. used four classification algorithms, namely kNN, RF, Decision Tree (DT), Gradient Boosting Decision Tree (GBDT), and AdaBoost, for classifying happy and sad emotional states using HR signals. SI analysis has been carried out for the classification and achieved the highest accuracy of

84% using the GBDT algorithm (SR09). The features extracted from the RSP signals have been used to classify joy and sadness emotional states using kNN classifier with SI analysis and achieved an accuracy of 85% (SR27).

Rakshit et al. have used the combination of SKT and PPG signals to classify happy and sad emotional states. The SD analysis carried out on combined signals yielded a maximum accuracy of 92.83% using the SVM classifier (SR05). Similarly, a combination of EDA and ECG signals is used to classify dichotomous emotions using SVM, NB, and kNN classifiers with SI analysis. The highest classification accuracy of 100% and 98.92% are achieved using EDA and ECG signals, correspondingly (SR32). Another multimodal study (combination of facial expressions and physiological signals (EEG and EDA)) conducted by Cimtay et al. has used SD analysis on the LUMED-2 database and SI analysis on the DEAP database. In both databases, the signals are recorded in SS. The SD analysis conducted on the signals collected from the LUMED-2 database achieves an accuracy of 53.80%. The SI analysis performed on the signals collected from the DEAP database achieves an accuracy of 75%.

Out of seven positive and negative emotion classification articles (SR33 – SR39), six articles have used EEG signals with machine learning algorithms, namely Multilayer Perceptron Neural Network (MLPNN), enhanced D-score Genetic Programming (eDGP), ELM, RF, sparse Autoencoder based Random Forest (ARF), Quadratic Discriminant Analysis (QDA), and combined Rotation Forest (RoF) with SVM. Among the EEG signal-based positive and negative emotion classification articles, the highest classification accuracy of 94.40% has been achieved using the ARF classifier and entropy-based feature. In this study, SI analysis has been carried out on the signals recorded in MS (SR36).

Two of the selected studies have used multiple databases for the analysis (SR35, SR37). An SI study has been conducted on EEG signals acquired in SS (from experiment and SEED database) and MS (DEAP database) using an eDGP classifier. The signals acquired from the experiment have achieved an accuracy of 86.55% (F-score - 0.9042), and the signals collected from the databases, namely DEAP and SEED, have achieved an accuracy of 84.81% and 86.22%, respectively (SR35). Similarly, Zheng et al. have used multiple databases, namely DEAP and SEED, to classify positive and negative emotional states using the ELM classification algorithm. The DEAP database has been created in SS, and the SEED database has been created in MS. The accuracy achieved by using EEG signals collected from the DEAP database is 69.67%, and the accuracy achieved by using EEG signals collected from the SEED database is 91.07%. SI analysis is carried out on the data collected from both databases (SR37).

In ECG, a SI analysis was carried out using an RF classifier and achieved an accuracy of 92.10%, 93.90%, and 92.20% for positive, negative, and neutral emotional states, respectively (SR38). The classifiers used in the selected studies and respective performance metrics obtained to classify dichotomous emotions are summarized in Table VI.

TABLE VII
THE SUMMARY OF THE SIGNIFICANCE LEVELS OBTAINED TO DIFFERENTIATE HAPPY AND SAD EMOTIONS

Modality	SR_id	Significance Level (p)
fEMG, PPG, HRV, EEG	SR01, SR02, SR11, SR12, SR25	≤ 0.01
HRV, EDA	SR08, SR28	≤ 0.001
EDA	SR16, SR23	≤ 0.05

$p \leq 0.05$ –>Significant; $p \leq 0.01$ –>Very significant; and $p \leq 0.001$ –> Highly significant

2) STATISTICAL ANALYSIS

Statistical analysis have been carried out in nine of the selected studies (SR01, SR02, SR08, SR11, SR12, SR16, SR23, SR25, SR28) to differentiate happy and sad emotional states. p-values are calculated to determine the significant features (SR12).

Type III ANOVA showed a significant difference in the mean of fEMG activated by the corrugator, orbicularis, and zygomaticus muscles (SR01). The time interval between foot, peak, and two successive feat of PPG signal are varied significantly high between happy and sad emotions (SR02). The frequency-domain indices of HRV, namely LF, HF, and LF to HF ratio, are highly significant to differentiate dichotomous emotions (SR08). The difference in the RI of the PPG signal for both happy and sad is very significant (SR11). Kolmogorov-Smirnov test showed a very significant variation in the PPE of HRV between happy and sad emotions (SR12).

Steenhaut et al. performed a pairwise t-test to know the emotional reactivity differences between younger and older adults using happy and sad film clips. In happy emotion, the tonic component of EDA varied significantly, and in sad emotion, VAS ratings of participants are varied significantly. For both happy and sad emotions, older adults reported higher reactivity (SR28).

Paired t-tests on EDA responses of the subjects in happy and sad emotions varied significantly (SR16). The CD of EEG signals in parietal and frontal regions showed a significant variation in differentiating joy and sadness (SR23). Similarly, the alpha patterns of EEG signals differed very significantly in happy and sad emotions (SR25). The summary of the significance levels obtained to differentiate happy and sad emotions are listed in Table VII.

III. DISCUSSION

Despite the fact that these emotional states can be easily measured using physiological traits, the needs for measurement can differ widely on the basis of user, technology, medical, and environment related factors. In this review, six physiological traits and the instruments used for measuring dichotomous emotional states are identified. Moreover, each instrument has been outlined on the basis of its user related properties (i.e., setup time, measurement intrusiveness, and size), medical related properties (i.e., invasive/non-invasive and safety), technological related properties (i.e., compatibility, input impedance, input voltage range, sensitivity, and SNR) and cost. Most of the instruments used in the reviewed articles may be ideal for measuring in a laboratory setting, but they may not be the preferential alternative for motion artifacts characterization in real-time applications.

When the number of electrodes is considered, the instrument must be designed with a fewer number of electrodes. Nevertheless, it requires a relatively large number of electrodes, for most current EEG devices [105]. The highest number of electrodes used for recording EEG signals in this review is 64 (SR03), whereas the minimum number is two when recording HR in (SR09). One study used continuous-wave Doppler radar for emotion recognition, where the user does not require to wear any sensor/electrode on the body (SR27).

In recent days, with the advancements in technology, wearable devices are popular for emotional state assessment in real time because of its unobtrusiveness and relatively long recording time [106]. Quiroz et al. have used a wearable Samsung Gear 2 device to record accelerometer and gyroscope sensor data from the participants and achieved an accuracy of 70% (SR06) and 76.30% (SR07) to classify happy and sad emotions. Emotive EPOC + headset has been used to record EEG signals and obtained an accuracy of 83.93% (SR10), 91.18% (SR17), and 87.50% (SR18) to classify dichotomous emotional states. Similarly, Jaswini et al. have used Enobio wearable device to classify happy and sad emotions from EEG signals with 63.63% and 100% accuracy, respectively (SR22). In one of the studies, Empatica E4 wristband has been used to acquire EDA signals participants and obtained an accuracy of 81.20% to classify two opposite emotions, namely happy and sad (SR29). Recently, Shu et al. used a wearable device, namely Algoband F8, to collect HR signals and classified happy and sad emotions with an accuracy of 84.00% (SR09). NeuroSky MindWave Mobile 2 headset wearable device have been used to acquire EEG signals and classified positive and negative emotional states with an accuracy of 87.61% (SR35).

Based on the reviewed articles, a single modality is commonly considered to recognize dichotomous emotional states. In comparison to a single modality, multiple modalities may provide better information and enhance recognition accuracy. The instruments such as the Multi-channel electrophysiological recording system - RM6240, HelathLab, and Biopac supports multiple physiological signal recordings. Thus, multiple modalities can be explored to classify emotional states.

The accuracy of dichotomous emotional state recognition can also be enhanced using multiple combinations of features and classifiers. The choice of feature extraction domain depends on the type of signal and its characteristics. The use of TF domain features is insufficiently explored in the selected articles. The various machine learning approaches such as SVM, RF, LDA, and Fisher have been used for the classification of happy and sad emotional states. The choice of classification algorithm mostly depends upon both the type modality and the type of application. In this review, SVM with time domain features is most commonly used. The use of deep learning methods can also be incorporated with the growing use of newly available machine learning and artificial intelligence tools.

IV. CONCLUSION

This study presents a review of sensing approaches in emotion recognition when dichotomous emotions are elicited using audio-visual stimuli using various protocols, recording devices, and classification methods. Performance evaluation is carried out among the devices used in the selected review articles, but there is a lack in the user related factors of the approaches considered. Despite the undisputed value of ambulatory diagnosis, the monitoring of happy-sad emotional states is not established. Most of the methods in this study mainly focused on the enhancement of emotion recognition accuracy using multiple combinations of features and classifiers. In order to increase the quality of life, critical developments in instrumentation are still actively sought to improve the efficiency of ambulatory care monitors. Thus, the research on the type of stimuli, features, and classification algorithms is still challenging with current enhancement in wearable emotion recognition devices. For a more effective recognition of happy and sad emotional states, the fusion of multiple physiological parameters are pursued for monitoring capability on wearable devices.

ACKNOWLEDGMENT

The authors would like to thank the lab mates, institute, and ministry of human resource and development for supporting the work.

REFERENCES

[1] J. Reeve, “Understanding Motivation and Emotion,” 7th ed., John Wiley & sons, 2014.

[2] P. Ekman, “An argument for basic emotions,” Cognition and Emotion, vol. 6, no. 3–4, pp. 169–200, May 1992, doi: 10.1080/02699939208411068.

[3] S. An, L.-J. Ji, M. Marks, and Z. Zhang, “Two Sides of Emotion: Exploring Positivity and Negativity in Six Basic Emotions across Cultures,” Front. Psychol., vol. 8, 2017, doi: 10.3389/fpsyg.2017.00610.

[4] M. A. Cohn, B. L. Fredrickson, S. L. Brown, J. A. Mikels, and A. M. Conway, “Happiness Unpacked: Positive Emotions Increase Life Satisfaction by Building Resilience,” Emotion, vol. 9, no. 3, pp. 361–368, Jun. 2009, doi: 10.1037/a0015952.

[5] R. J. Larsen and E. Diener, “Promises and problems with the circumplex model of emotion,” In M. S. Clark (Ed.), Review of personality and soc. psychology: Emotion (13, pp. 25-59). Newbury Park, CA: Sage, 1992.

[6] J. Russell and L. Barrett, “Core affect, prototypical emotional episodes, and other things called emotion: Dissecting the elephant,” Journal of personality and social psychology, vol. 76, pp. 805–19, Jun. 1999, doi: 10.1037//0022-3514.76.5.805.

[7] J. A. Russell, “A circumplex model of affect,” Journal of Personality and Social Psychology, vol. 39, no. 6, pp. 1161–1178, 1980, doi: 10.1037/h0077714.

[8] T. Treffers, P. Klarner, and Q. N. Huy, “Emotions, time, and strategy: The effects of happiness and sadness on strategic decision-

making under time constraints," Long Range Planning, vol. 53, no. 5, p. 101954, Oct. 2020, doi: 10.1016/j.lrp.2019.101954.
[9] J. Burgdorf and J. Panksepp, "The neurobiology of positive emotions," Neuroscience & Biobehavioral Reviews, vol. 30, no. 2, pp. 173–187, Jan. 2006, doi: 10.1016/j.neubiorev.2005.06.001.
[10] S. Lyubomirsky, L. King, and E. Diener, "The Benefits of Frequent Positive Affect: Does Happiness Lead to Success?," Psychol. Bull., vol. 131, no. 6, pp. 803–855, 2005, doi: 10.1037/0033-2909.131.6.803.
[11] N. Vanlessen, R. De Raedt, E. H. W. Koster, and G. Pourtois, "Happy heart, smiling eyes: A systematic review of positive mood effects on broadening of visuospatial attention," Neuroscience & Biobehavioral Reviews, vol. 68, pp. 816–837, Sep. 2016, doi: 10.1016/j.neubiorev.2016.07.001.
[12] F. Dolcos et al., "Neural correlates of emotion-attention interactions: From perception, learning, and memory to social cognition, individual differences, and training interventions," Neuroscience & Biobehavioral Reviews, vol. 108, pp. 559–601, Jan. 2020, doi: 10.1016/j.neubiorev.2019.08.017.
[13] J. A. Arias et al., "The neuroscience of sadness: A multidisciplinary synthesis and collaborative review," Neuroscience & Biobehavioral Reviews, vol. 111, pp. 199–228, Apr. 2020, doi: 10.1016/j.neubiorev.2020.01.006.
[14] Y. Millgram, J. Joormann, J. D. Huppert, A. Lampert, and M. Tamir, "Motivations to Experience Happiness or Sadness in Depression: Temporal Stability and Implications for Coping With Stress:," Clinical Psychological Science, Oct. 2018, doi: 10.1177/2167702618797937.
[15] N. Srinivasan and A. Hanif, "Global-happy and local-sad: Perceptual processing affects emotion identification," Cognition and Emotion, vol. 24, no. 6, pp. 1062–1069, Sep. 2010, doi: 10.1080/02699930903101103.
[16] H. N. Lokko and T. A. Stern, "Sadness: Diagnosis, Evaluation, and Treatment," Prim Care Companion CNS Disord, vol. 16, no. 6, Nov. 2014, doi: 10.4088/PCC.14f01709.
[17] J. F. Helliwell, R. Layard, J. Sachs, and J.-E. De Neve, "Changing world happiness," World Happiness Report 2019, pp.11-46, 2019.
[18] World Health Organization, 2011. World Health Organization 2011 Fact Sheet on Cardiovascular Disease Available at: http://www.who.int/mediacentre/factsheets/fs317/en/index.html.
[19] S. Jain, U. Oswal, K. S. Xu, B. Eriksson, and J. Haupt, "A Compressed Sensing Based Decomposition of Electrodermal Activity Signals," IEEE Transactions on Biomedical Engineering, vol. 64, no. 9, pp. 2142–2151, Sep. 2017, doi: 10.1109/TBME.2016.2632523.
[20] Y.R. Veeranki, N. Ganapathy, and R. Swaminathan. "Non-Parametric Classifiers Based Emotion Classification Using Electrodermal Activity and Modified Hjorth Features," Studies in Health Technology and Informatics, vol. 281, pp.163-167, May 2021, doi:10.3233/SHTI210141
[21] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks," IEEE Transactions on Affective Computing, Vol. 11, no. 3, pp. 532–541, 2018, doi: 10.1109/TAFFC.2018.2817622.
[22] A.-L. Gilet and C. Jallais, "Valence, arousal and word associations," Cognition and Emotion, vol. 25, no. 4, pp. 740–746, Jun. 2011, doi: 10.1080/02699931.2010.500480.
[23] J. P. Machado-de-Sousa et al., "Facial affect processing in social anxiety: Tasks and stimuli," Journal of Neuroscience Methods, vol. 193, no. 1, pp. 1–6, Oct. 2010, doi: 10.1016/j.jneumeth.2010.08.013.
[24] M. I. Singh and M. Singh, "Development of a real time emotion classifier based on evoked EEG," Biocybernetics and Biomedical Engineering, vol. 37, no. 3, pp. 498–509, Jan. 2017, doi: 10.1016/j.bbe.2017.05.004.
[25] N. Ganapathy, Y. R. Veeranki, and R. Swaminathan, "Convolutional neural network based emotion classification using electrodermal activity signals and time-frequency features," Expert Systems with Applications, vol. 159, p. 113571, Nov. 2020, doi: 10.1016/j.eswa.2020.113571.
[26] V. Sharma, N. R. Prakash, and P. Kalra, "Audio-video emotional response mapping based upon Electrodermal Activity," Biomedical Signal Processing and Control, vol. 47, pp. 324–333, Jan. 2019, doi: 10.1016/j.bspc.2018.08.024.
[27] Y. Gao, X. Wang, T. Potter, J. Zhang, and Y. Zhang, "Single-trial EEG emotion recognition using Granger Causality/Transfer Entropy analysis," Journal of Neuroscience Methods, vol. 346, p. 108904, Dec. 2020, doi: 10.1016/j.jneumeth.2020.108904.
[28] S.-Y. Han, N.-S. Kwak, T. Oh, and S.-W. Lee, "Classification of pilots' mental states using a multimodal deep learning network," Biocybernetics and Biomedical Engineering, vol. 40, no. 1, pp. 324–336, Jan. 2020, doi: 10.1016/j.bbe.2019.12.002.
[29] N. Ganapathy, Y. R. Veeranki, H. Kumar, and R. Swaminathan, "Emotion Recognition Using Electrodermal Activity Signals and Multiscale Deep Convolutional Neural Network," J Med Syst, vol. 45, no. 4, p. 49, Mar. 2021, doi: 10.1007/s10916-020-01676-6.
[30] M. Destephe, T. Maruyama, M. Zecca, K. Hashimoto, and A. Takanishi, "The influences of emotional intensity for happiness and sadness on walking," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2013, pp. 7452–7455, 2013, doi:10.1109/EMBC.2013.6611281.
[31] M. Destephe, M. Zecca, K. Hashimoto, and A. Takanishi, "Conveying emotion intensity with bio-inspired expressive walking - Experiments with sadness and happiness," in 2013 IEEE RO-MAN, Aug. 2013, pp. 161–166, doi: 10.1109/ROMAN.2013.6628438.
[32] J. Michalak, N. F. Troje, J. Fischer, P. Vollmar, T. Heidenreich, and D. Schulte, "Embodiment of Sadness and Depression—Gait Patterns Associated With Dysphoric Mood," Psychosomatic Medicine, vol. 71, no. 5, pp. 580–587, Jun. 2009, doi: 10.1097/PSY.0b013e3181a2515c.
[33] L. Omlor and M. A. Giese, "Extraction of spatio-temporal primitives of emotional body expressions," Neurocomputing, vol. 70, no. 10, pp. 1938–1942, Jun. 2007, doi: 10.1016/j.neucom.2006.10.100.
[34] N. Sharif and P. Dehghani, "Acute pericarditis, myocarditis, and worse!," Can Fam Physician, vol. 59, no. 1, pp. 39–41, Jan. 2013.
[35] G. E. Schwartz, D. A. Weinberger, and J. A. Singer, "Cardiovascular differentiation of happiness, sadness, anger, and fear following imagery and exercise," Psychosomatic Medicine, vol. 43, no. 4, pp. 343–364, 1981, doi: 10.1097/00006842-198108000-00007.
[36] W. J. Kop, S. J. Synowski, M. E. Newell, L. A. Schmidt, S. R. Waldstein, and N. A. Fox, "Autonomic nervous system reactivity to positive and negative mood induction: The role of acute psychological responses and frontal electrocortical activity," Biological Psychology, vol. 86, no. 3, pp. 230–238, Mar. 2011, doi: 10.1016/j.biopsycho.2010.12.003.
[37] R. W. Levenson, "The Autonomic Nervous System and Emotion:," Emotion Review, Mar. 2014, doi: 10.1177/1754073913512003.
[38] S. Z. H. Kazmi et al., "Inverse Correlation between Heart Rate Variability and Heart Rate Demonstrated by Linear and Nonlinear Analysis," PLOS ONE, vol. 11, no. 6, p. e0157557, Jun. 2016, doi: 10.1371/journal.pone.0157557.
[39] I. Minio-Paluello, G. Porciello, M. Gandolfo, S. Boukarras, and S. M. Aglioti, "The enfacement illusion boosts facial mimicry," Cortex, vol. 123, pp. 113–123, Feb. 2020, doi: 10.1016/j.cortex.2019.10.001.
[40] B. Seibt, A. Mühlberger, K. U. Likowski, and P. Weyers, "Facial mimicry in its social setting," Front Psychol, vol. 6, Aug. 2015, doi: 10.3389/fpsyg.2015.01122.
[41] J. C. Britton, S. F. Taylor, K. C. Berridge, J. A. Mikels, and I. Liberzon, "Differential subjective and psychophysiological responses to socially and nonsocially generated emotional stimuli," Emotion, vol. 6, no. 1, pp. 150–155, 2006, doi: 10.1037/1528-3542.6.1.150.
[42] F. Li, L. Yang, H. Shi, and C. Liu, "Differences in photoplethysmography morphological features and feature time series between two opposite emotions: Happiness and sadness," Artery Research, vol. 18, pp. 7–13, Feb. 2017, doi: 10.1016/j.artres.2017.02.003.
[43] M. Y. V. Bekkedal, J. Rossi, and J. Panksepp, "Human brain EEG indices of emotions: Delineating responses to affective vocalizations by measuring frontal theta event-related

synchronization," Neuroscience & Biobehavioral Reviews, vol. 35, no. 9, pp. 1959–1970, Oct. 2011, doi: 10.1016/j.neubiorev.2011.05.001.

[44] F. S. de Aguiar Neto and J. L. G. Rosa, "Depression biomarkers using non-invasive EEG: A review," Neuroscience & Biobehavioral Reviews, vol. 105, pp. 83–93, Oct. 2019, doi: 10.1016/j.neubiorev.2019.07.021.

[45] M. Asahina, A. Poudel, and S. Hirano, "Sweating on the palm and sole: physiological and clinical relevance," Clin. Auton. Res., vol. 25, no. 3, pp. 153–159, Jun. 2015, doi: 10.1007/s10286-015-0282-1.

[46] M. Benedek and C. Kaernbach, "A continuous measure of phasic electrodermal activity," Journal of Neuroscience Methods, vol. 190, no. 1, pp. 80–91, Jun. 2010, doi: 10.1016/j.jneumeth.2010.04.028.

[47] Y. Hu, C. Converse, M. C. Lyons, and W. H. Hsu, "Neural control of sweat secretion: a review," British Journal of Dermatology, vol. 178, no. 6, pp. 1246–1256, 2018, doi: 10.1111/bjd.15808.

[48] M. T. Quazi, "Human Emotion Recognition Using Smart Sensors," Palmerston North, Feb. 2012.

[49] S. Khalfa, M. Roy, P. Rainville, S. Dalla Bella, and I. Peretz, "Role of tempo entrainment in psychophysiological differentiation of happy and sad music?," International Journal of Psychophysiology, vol. 68, no. 1, pp. 17–26, Apr. 2008, doi: 10.1016/j.ijpsycho.2007.12.001.

[50] T. Brosch, G. Pourtois, and D. Sander, "The perception and categorisation of emotional stimuli: A review," Cognition and Emotion, vol. 24, no. 3, pp. 377–400, Apr. 2010, doi: 10.1080/02699930902975754.

[51] D. Grühn and N. Sharifian, "7 - Lists of Emotional Stimuli," in Emotion Measurement, H. L. Meiselman, Ed. Woodhead Publishing, 2016, pp. 145–164. doi: 10.1016/B978-0-08-100508-8.00007-2.

[52] D. Grühn and S. Scheibe, "Age-related differences in valence and arousal ratings of pictures from the International Affective Picture System (IAPS): Do ratings become more extreme with age?," Behavior Research Methods, vol. 40, no. 2, pp. 512–521, May 2008, doi: 10.3758/BRM.40.2.512.

[53] D. Grühn, J. Smith, and P. B. Baltes, "No aging bias favoring memory for positive material: Evidence from a heterogeneity-homogeneity list paradigm using emotionally toned words.," Psychology and Aging, vol. 20, no. 4, pp. 579–588, 2005, doi: 10.1037/0882-7974.20.4.579.

[54] R. Westermann, K. Spies, G. Stahl, and F. W. Hesse, "Relative effectiveness and validity of mood induction procedures: a meta-analysis," European Journal of Social Psychology, vol. 26, no. 4, pp. 557–580, 1996, doi: 10.1002/(SICI)1099-0992(199607)26:4<557::AID-EJSP769>3.0.CO;2-4.

[55] B. W. Gawali, S. Rao, P. Abhang, P. Rokade, and S. C. Mehrotra,"Classification of EEG signals for different emotional states," in 4th International in Proc. ARTCom, 2012, pp. 177–181, doi:10.1049/cp.2012.2521.

[56] A. Khasnobish et al., "The Role of Empirical Mode Decomposition on Emotion Classification Using Stimulated EEG Signals," in Advances in Computing and Information Technology, vol. 178, N. Meghanathan, D. Nagamalai, and N. Chaki, Eds.Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 55–62. doi: 10.1007/978-3-642-31600-5_6.

[57] M. W. Park, C. J. Kim, M. Hwang, and E. C. Lee, "Individual Emotion Classification between Happiness and Sadness by Analyzing Photoplethysmography and Skin Temperature," in 2013 Fourth World Congress on Software Engineering, Hong Kong, China, Dec. 2013, pp. 190–194, doi: 10.1109/WCSE.2013.34.

[58] J. C. Quiroz, M. H. Yong, and E. Geangu, "Emotion-recognition using smart watch accelerometer data: preliminary findings," in Proc. UbiComp '17, Maui, Hawaii, 2017, pp. 805–812, doi:10.1145/3123024.3125614.

[59] J. C. Quiroz, E. Geangu, and M. H. Yong, "Emotion Recognition Using Smart Watch Sensor Data: Mixed-Design Study," JMIR Ment. Health, vol. 5, no. 3, p. e10153, Aug. 2018, doi:10.2196/10153.

[60] H. Shi et al., "Differences of Heart Rate Variability Between Happiness and Sadness Emotion States: A Pilot Study," J. Med. Biol. Eng., vol. 37, no. 4, pp. 527–539, Aug. 2017, doi: 10.1007/s40846-017-0238-0.

[61] L. Shu et al., "Wearable Emotion Recognition Using Heart Rate Data from a Smart Bracelet," Sensors, vol. 20, no. 3, p. 718, Jan. 2020, doi: 10.3390/s20030718.

[62] A. Singhal, P. Kumar, R. Saini, P. P. Roy, D. P. Dogra, and B.-G. Kim, "Summarization of videos by analyzing affective state of the user through crowdsource," Cognitive Systems Research, vol. 52, pp. 917–930, Dec. 2018, doi: 10.1016/j.cogsys.2018.09.019.

[63] Y. Xia, L. Yang, X. Mao, D. Zheng, and C. Liu, "Quantification of vascular function changes under different emotion states: A pilot study," THC, vol. 25, no. 3, pp. 447–456, Jun. 2017, doi: 10.3233/THC-161284.

[64] Y. Xia, L. Yang, H. Shi, Y. Zhuang, and C. Liu, "Changes of Permutation Pattern Entropy and Ordinal Pattern Entropy During Three Emotion States: Natural, Happiness and Sadness," in Computing in Cardiology Conference, Sep. 2017. doi: 10.22489/CinC.2017.317-457.

[65] X. Xu, Y. Zhang, M. Tang, H. Gu, S. Yan, and J. Yang, "Emotion Recognition Based on Double Tree Complex Wavelet Transform and Machine Learning in Internet of Things," IEEE Access, vol. 7, pp. 154114–154120, 2019, doi: 10.1109/ACCESS.2019.2948884.

[66] G. Liu, "Detrended Fluctuation Analysis Based on the Affective ECG," JFBI, vol. 7, no. 1, pp. 91–102, Jun. 2014, doi: 10.3993/jfbi03201408.

[67] Y. Liu and C. Jiang, "Recognition of Shooter's Emotions Under Stress Based on Affective Computing," IEEE Access, vol. 7, pp. 62338–62343, 2019, doi: 10.1109/ACCESS.2019.2916147.

[68] J. F. Christensen, A. Gomila, S. B. Gaigg, N. Sivarajah, and B. Calvo-Merino, "Dance expertise modulates behavioral and psychophysiological responses to affective body movement," J Exp Psychol Hum Percept Perform, vol. 42, no. 8, pp. 1139–1147, Aug. 2016, doi: 10.1037/xhp0000176.

[69] Q. Gao, C. Wang, Z. Wang, X. Song, E. Dong, and Y. Song, "EEG based emotion recognition using fusion feature extraction method," Multimed Tools Appl, vol. 79, no. 37–38, pp. 27057–27074, Oct. 2020, doi: 10.1007/s11042-020-09354-y.

[70] N. Y. Oktavia, A. D. Wibawa, E. S. Pane, and M. H. Purnomo, "Human Emotion Classification Based on EEG Signals Using Naïve Bayes Method," in International Seminar on Application for Technology of Information and Communication (iSemantic), Semarang, Indonesia, Sep. 2019, pp. 319–324. doi: 10.1109/ISEMANTIC.2019.8884224.

[71] I. Mazumder, "An Analytical Approach of EEG Analysis for Emotion Recognition," in Devices for Integrated Circuit (DevIC), Kalyani, India, Mar. 2019, pp. 256–260. doi: 10.1109/DEVIC.2019.8783331.

[72] A. H. Krishna, A. B. Sri, K. Y. V. S. Priyanka, S. Taran, and V. Bajaj, "Emotion classification using EEG signals based on tunable-Q wavelet transform," IET Science, Measurement & Technology, vol. 13, no. 3, pp. 375–380, May 2019, doi: 10.1049/iet-smt.2018.5237.

[73] R. Nivedha, M. Brinda, D. Vasanth, M. Anvitha, and K. V. Suma, "EEG based emotion recognition using SVM and PSO," in International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Jul. 2017, pp. 1597–1600. doi: 10.1109/ICICICT1.2017.8342809.

[74] T. Jaswini S and K. M Ravikumar, "Detection of human emotions using features based on discrete wavelet transforms of EEG signals," IJET, vol. 7, no. 1.9, p. 119, Mar. 2018, doi: 10.14419/ijet.v7i1.9.9746.

[75] S. Hatamikia, A. M. Nasrabadi, and N. Shourie, "Analysis of inter-hemispheric and intra-hemispheric differences of the correlation dimension in the emotional states based on EEG signals," in 22nd Iranian Conference on Biomedical Engineering (ICBME), Tehran, Iran, Nov. 2015, pp. 6–9. doi: 10.1109/ICBME.2015.7404106.

[76] H. Candra, M. Yuwono, A. Handojoseno, R. Chai, S. Su, and H. T. Nguyen, "Recognizing emotions from EEG subbands using wavelet analysis," in Annu Int Conf IEEE Eng Med Biol Soc, vol. 2015, pp. 6030–6033, 2015, doi: 10.1109/EMBC.2015.7319766.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

[77] P. S. Vinayak, S. K. Dhanoa, and D. A. A.- Sisode, “Emotions and Brain Waves,” Int. j. Indian psychol., vol. 3, no. 2, Mar. 2016, doi: 10.25215/0302.075.

[78] R. Rakshit, V. R. Reddy, and P. Deshpande, “Emotion detection and recognition using HRV features derived from photoplethysmogram signals,” in Proceedings of the 2nd workshop on Emotion Representations and Modelling for Companion Systems, New York, NY, USA, Nov. 2016, pp. 1–6. doi: 10.1145/3009960.3009962.

[79] Q. Gao et al., “Non-Contact Emotion Recognition via CW Doppler Radar,” in 2018 Asia-Pacific Microwave Conference (APMC), Kyoto, Nov. 2018, pp. 1468–1470. doi: 10.23919/APMC.2018.8617402.

[80] P. Steenhaut, I. Demeyer, R. De Raedt, and G. Rossi, “The Role of Personality in the Assessment of Subjective and Physiological Emotional Reactivity: A Comparison Between Younger and Older Adults,” Assessment, vol. 25, no. 3, pp. 285–301, Apr. 2018, doi: 10.1177/1073191117719510.

[81] Y. Cimtay, E. Ekmekcioglu, and S. Caglar-Ozhan, “Cross-Subject Multimodal Emotion Recognition Based on Hybrid Fusion,” IEEE Access, vol. 8, pp. 168865–168878, 2020, doi: 10.1109/ACCESS.2020.3023871.

[82] P. Chettupuzhakkaran and N. Sindhu, “Emotion Recognition from Physiological Signals Using Time-Frequency Analysis Methods,” in International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR), Jul. 2018, pp. 1–5. doi: 10.1109/ICETIETR.2018.8529145.

[83] P. Lahane and M. Thirugnanam, “A novel approach for analyzing human emotions based on electroencephalography (EEG),” in Innovations in Power and Advanced Computing Technologies (i-PACT), Apr. 2017, pp. 1–6. doi: 10.1109/IPACT.2017.8245056.

[84] P. Das, A. Khasnobish, and D. N. Tibarewala, “Emotion recognition employing ECG and GSR signals as markers of ANS,” in Conference on Advances in Signal Processing (CASP), Jun. 2016, pp. 37–42. doi: 10.1109/CASP.2016.7746134.

[85] M. S. Özerdem and H. Polat, “Emotion recognition based on EEG features in movie clips with channel selection,” Brain Inf., vol. 4, no. 4, pp. 241–252, Dec. 2017, doi: 10.1007/s40708-017-0069-3.

[86] A. Subasi, T. Tuncer, S. Dogan, D. Tanko, and U. Sakoglu, “EEG-based emotion recognition using tunable Q wavelet transform and rotation forest ensemble classifier,” Biomedical Signal Processing and Control, vol. 68, p. 102648, Jul. 2021, doi: 10.1016/j.bspc.2021.102648.

[87] D. Acharya et al., “An enhanced fitness function to recognize unbalanced human emotions data,” Expert Systems with Applications, vol. 166, p. 114011, Mar. 2021, doi: 10.1016/j.eswa.2020.114011.

[88] A. Bhattacharyya, R. K. Tripathy, L. Garg, and R. B. Pachori, “A Novel Multivariate-Multiscale Approach for Computing EEG Spectral and Temporal Complexity for Human Emotion Recognition,” IEEE Sensors Journal, vol. 21, no. 3, pp. 3579–3591, Feb. 2021, doi: 10.1109/JSEN.2020.3027181.

[89] W.-L. Zheng, J.-Y. Zhu, and B.-L. Lu, “Identifying Stable Patterns over Time for Emotion Recognition from EEG,” IEEE Trans. Affective Comput., vol. 10, no. 3, pp. 417–429, Jul. 2019, doi: 10.1109/TAFFC.2017.2712143.

[90] D. N. K. Hardani, O. Wahyunggoro, H. A. Nugroho, and N. Faisal, “Analysis of emotional condition based on electrocardiogram signals,” in International Conference on Electrical Engineering and Computer Science (ICEECS), Kuta, Bali, Indonesia, Nov. 2014, pp. 152–157. doi: 10.1109/ICEECS.2014.7045236.

[91] Y.-Y. Lee and S. Hsieh, “Classifying Different Emotional States by Means of EEG-Based Functional Connectivity Patterns,” PLoS ONE, vol. 9, no. 4, p. e95415, Apr. 2014, doi: 10.1371/journal.pone.0095415.

[92] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and T. P. Group, “Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement,” PLOS Medicine, vol. 6, no. 7, p. e1000097, Jul. 2009, doi: 10.1371/journal.pmed.1000097.

[93] L. Fernández-Aguilar, J. Ricarte, L. Ros, and J. M. Latorre, “Emotional Differences in Young and Older Adults: Films as Mood Induction Procedure,” Front. Psychol., vol. 9, 2018, doi: 10.3389/fpsyg.2018.01110.

[94] R. Khandpur, Biomedical Instrumentation: Technology and Applications. Mcgraw-hill, 2004.

[95] J. G. Webster, Medical Instrumentation: Application and Design. John Wiley & Sons, 2009.

[96] D. Girardi, F. Lanubile, and N. Novielli, “Emotion detection using noninvasive low cost sensors,” in 7th International Conference on Affective Computing and Intelligent Interaction (ACII), Oct. 2017, pp. 125–130. doi: 10.1109/ACII.2017.8273589.

[97] R. W. Picard, Toward Machines with Emotional Intelligence. In ICINCO , pp. 29-30. 2004.

[98] S. Hwang, H. Jebelli, B. Choi, M. Choi, and S. Lee, “Measuring Workers’ Emotional State during Construction Tasks Using Wearable EEG,” Journal of Construction Engineering and Management, vol. 144, no. 7, p. 04018050, Jul. 2018, doi: 10.1061/(ASCE)CO.1943-7862.0001506.

[99] N. S. Williams, G. M. McArthur, B. de Wit, G. Ibrahim, and N. A. Badcock, “A validation of Emotiv EPOC Flex saline for EEG and ERP research,” PeerJ, vol. 8, Aug. 2020, doi: 10.7717/peerj.9713.

[100] F. R. Parente et al., “An Electronic System for the Contactless Reading of ECG Signals,” Sensors (Basel), vol. 17, no. 11, Oct. 2017, doi: 10.3390/s17112474.

[101] M. Egger, M. Ley, and S. Hanke, “Emotion Recognition from Physiological Signal Analysis: A Review,” Electronic Notes in Theoretical Computer Science, vol. 343, pp. 35–55, May 2019, doi: 10.1016/j.entcs.2019.04.009.

[102] M.-Z. Poh, N. C. Swenson, and R. W. Picard, “A Wearable Sensor for Unobtrusive, Long-Term Assessment of Electrodermal Activity,” IEEE Transactions on Biomedical Engineering, vol. 57, no. 5, pp. 1243–1252, May 2010, doi: 10.1109/TBME.2009.2038487.

[103] G. C. Pope and R. J. Halter, “Design and Implementation of an Ultra-Low Resource Electrodermal Activity Sensor for Wearable Applications,” Sensors, vol. 19, no. 11, Art. no. 11, Jan. 2019, doi: 10.3390/s19112450.

[104] D. Castaneda, A. Esparza, M. Ghamari, C. Soltanpur, and H. Nazeran, “A review on wearable photoplethysmography sensors and their potential future applications in health care,” Int J Biosens Bioelectron, vol. 4, no. 4, pp. 195–202, 2018, doi: 10.15406/ijbsbe.2018.04.00125.

[105] A. Al-Nafjan, M. Hosny, Y. Al-Ohali, and A. Al-Wabil, “Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review,” Applied Sciences, vol. 7, no. 12, p. 1239, Dec. 2017, doi: 10.3390/app7121239.

[106] T. K. L. Hui and R. S. Sherratt, “Coverage of Emotion Recognition for Common Wearable Biosensors,” Biosensors (Basel), vol. 8, no. 2, Mar. 2018, doi: 10.3390/bios8020030.

YEDUKONDALA RAO VEERANKI received his B.Tech. and M.Tech. Degrees in Electronics and Communication Engineering. He is currently pursuing his Ph.D. Degree in Biomedical Engineering in the Department of Applied Mechanics at Indian Institute of Technology Madras, India. His research interests include Biomedical Signal Processing and Machine Learning Applied to Emotion Detection and Classification.

HIMANSHU KUMAR received his B.Tech. and M.Tech. Degrees in Biomedical Engineering. He is currently pursuing his Ph.D. Degree in Biomedical Engineering in the Department of Applied Mechanics at Indian Institute of Technology Madras, India. His research interests include Biomedical Signal Processing, Computational Neuroscience and Emotion Recognition using EEG and EDA.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3110773, IEEE Access

NAGARAJAN GANAPATHY (Member, IEEE) has received his Ph.D. degree in Biomedical Engineering from Indian Institute of Technology Madras, India. He is currently a research fellow in PLRI for Medical Informatics of TU Braunschweig and Hannover Medical School, Germany. His research interests include Artificial Intelligence, Deep Learning, Signal and Image Analytics, Wearables Systems, Affective Computing and Behavioral Informatics.

BALASUBRAMANIAM NATARAJAN (Senior Member, IEEE) is a Clair N. Palmer and Sara M. Palmer Endowed Professor and the Director of the Wireless Communication and Information Processing Research Group, Kansas State University, USA. His research interests include Statistical Signal Processing, Stochastic Modeling, Optimization, and Control Theories. He has published more than 200 refereed Journal and Conference papers. He has served on the editorial board for multiple IEEE journals including the IEEE Transactions on Wireless Communications.

RAMAKRISHNAN SWAMINATHAN (Member, IEEE) is the Professor in Biomedical Engineering and Head of the Department of Applied Mechanics, Indian Institute of Technology Madras, India. His current areas of research include Biomedical Instrumentation, Biomedical Signal Processing Applied to Pregnancy Monitoring and Emotion Detection. He has supervised more than 25 research scholars and has authored over 375 papers in Journals and Conferences. Currently, he is engaged in the establishment of Centre of Excellence for Medical Device Regulations and Standards at Indian Institute of Technology Madras, India.