Automated Distress Detection: A Review

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I. Introduction

Distress is considered as emotional suffering with high global prevalence, which can result in disabling conditions and impairment for patients. It is a major health problem, both in developing and developed nations, accounting for one-third of disability adjusted life years (DALYs) [1]. Patients with distress mostly go undetected or receive no treatment even in high-income economies with well-developed healthcare system [2]. Due to the absence of standard assessment tools, the prevalence of distress is difficult to measure exactly, however, it roughly ranges between 5% and 27% in general population [3], [4]. Distress can be caused due to stressful work at office [5], family responsibilities [6], lower socioeconomic position [7], [8] chronic diseases [9], study burden [1], fall or any other physical threat especially in elderly [10], victimisation in a crime [11] and so on. Patients with chronic disease such as cancer patients perhaps face the most severe level of distress in all stages of life. Most of the time cancer related distress goes undetected, which leads to severe negative consequences including depression, anxiety, isolation, panic, and suicidal ideation. This often complicates the treatment, increasing the cost of cancer care by as much as 20% [12], [13]. Therefore, timely identification of distress is crucial for the management of patients with distress.

Generally, screening is considered as a quick examination to identify individuals who need additional services such as referral, comprehensive assessment, or treatment by a specialised professional. It can potentially reduce healthcare cost by providing earlier identification and intervention of disease. However, screening tools and instruments for distress identification are rarely used in clinical setting [14] and when used provides unsatisfactory results mainly due to the inability of patients to report their symptoms correctly [15] and unavailability of evidence-based psychosocial interventions [16]. In addition, most of these screening tools are quite time consuming [17]. This is further compounded by the fact that distress itself is a complex phenomenon to measure using the screening tools [6]. The symptoms included in these tools are predominately based on depression and anxiety; but, can also be likened to somatic symptoms (insomnia, headaches, and lack of energy) and are likely to vary among different cultures [18].

Undoubtedly, earlier identification of distress can enable an effective way of handling distressed patients and reduce the risk of complicated mental disorders. However, the shortcomings of the existing distress screening tools make early identification challenging. Most of these tools are primarily focused on post distress conditions such as depression, anxiety, Post-traumatic stress disorder (PTSD), and suicidal behaviour identification. This trend needs to be re-imagined because if distress can be detected in the earlier stage, the consequences (depression, anxiety, suicidal ideation) might not happen in the first place. Automating the distress detection can alleviate many of challenges of the existing screening tools, however, there are also a number of challenges need to be addressed to develop a robust automated distress detection system. In this paper, we aim to provide critiques on distress detection research in terms of assessment tools, available datasets and existing methods for automatic distress screening. A number of studies [19]–[21] have reviewed the research on automatic depression detection but none of them has highlighted the research gap for distress detection. This study attempts to highlight the core differences of distress from other emotions and mental disorders, discuss existing methodologies for inferring distress and provide future directions for developing an automated distress system.

II. What is Distress

Distress is considered as a continuum of psychological symptoms with varying severity [22]. In areas like forensic the term "distress" is specifically used for the affective states that arise in violent situations. The National Comprehensive Cancer Network provides the widely accepted definition of distress [23]: *Distress is a multifactorial unpleasant emotional experience of a psychological (cognitive, behavioural, emotional), social, and/or spiritual nature. Distress encompass a range of common feelings of vulnerability, sadness, and fears that can cause depression, anxiety, panic, social isolation, and existential and spiritual crisis.* Distress may not always be caused by some unexpected external events, but can also be caused by internal states such as feelings, thoughts, and habitual behaviours. It is an uncomfortable feeling and can impact individuals' capacity of working, social life, bodily part and the mind. It is a subjective experience, and different people manifest it differently with varied range of symptoms. However, the most common symptoms [24] of distress are: sleep disturbances, memory problems, anger management issues, obsessive thoughts, fatigue, sadness, weight gain, hallucinations, delusions, etc.

A. How Distress is different from Emotions

Emotion is an essential component of human life and plays important role for their survival [25]. As a human being, we feel a whole range of emotions that may be comfortable or uncomfortable [26], [27]. Emotional discomfort is a universal human experience. In fact, negative emotions including sadness, anger and fear are important and useful in various situations. For instance, fear is helpful when there is real threat to our safety (e.g., gun pointed at us or wild ferocious animal coming). It helps humans to effectively withstand such threatening situations. Similarly, sadness inadvertently helps in spotlighting the things that we care about in our life. It is however very important to note that negative emotions are not necessarily distress [28], for example: disgust [29].

In our daily life, emotions act like a wave as they are always fluctuating, reaching some plateau, and eventually subside and pass. In other words, emotions are transient, they just move and change. In contrast, distress is a prevailing situation that, if not addressed, it goes on, gets worse and worse until emotional combust [28]. Emotions such as fear or anger are aroused to prevent, solve, cope with, or get away from specific situation. However, distressed situations are felt strongly and often difficult to cope with [30].

B. How Distress is different from Stress

Often stress and distress are used interchangeably, which blurs and confuses the distinctions between these concepts [31]. It is however important to distinguish these two terms. Stress is an important element of life, as it has both positive and negative effect. As pointed by Spielberger [32], *"Stress is an integral part of the natural fabric of life, and coping with stress is an everyday requirement for normal human growth and development"*. The body uses behavioural or physiological mechanisms to counter the perturbation caused by stress and come back to normality. People can adapt stress but when stress is not adapted or coped for a long time it may change to distress. It can also become both chronic and acute stress [33]. The transition of stress to distress depends on various factors including duration, intensity, and controllability.

C. How Distress is different from Depression

Other dimensions of psychopathology such as depression and anxiety are also closely related to distress. In particular, most assessment tools and treatment of distress is based on the depression symptoms [34]. Patients with depression need to meet at least five of the DSM-5 (Diagnostic and Statistical Manual of Mental Disorder, Fifth Edition) criterion for major depressive disorder nearly every day during 2-week period. However, distress has different symptoms such as poor self-management, feeling angry and scared, and feeling of unsupported by family and friends [35], which are not included in DSM-5. This suggests the need to formulate an alternative screening for distressed people, who are not clinically depressed.

III. Assessment Scales

Distress remains undetected in most patients [44], however, surprisingly, there are many scales available to gauge distress. In this section we present the most popular scales used to screen distress. We also present (see Table I) the number of questions/items in each scale and time to conduct the screening to indicate the complexity of each scale.

Disability Distress Assessment Tool (DisDAT) [45] is designed by a palliative care team for distress assessment. It is not a scoring tool, rather it documents a wide range of behaviours and signs related to distress. A distress scale based on ten symptoms was designed by Mccorkle et al. [39]. This scale was tested on 53 patients, where distress score was ranged from 10-41. Distress Thermometer [46], is another scale which enables patients to rate their distress level on visual scale ranging from 0 (no distress) to 10 (extreme distress). The SCL-90 (Symptom Checklist-90) and BSI (Brief Symptom Inventory) have been widely used for screening of psychological distress in medical patients, and demonstrated high levels of specificity and sensitivity [22], [47]. The 12-item General Health Questionnaire (GHQ-12) is designed to study of psychological disorders in general clinical setting. It is also used for distress screening in various studies [48], [49]. A recently proposed scale for distress assessment is the K10 [50]. It is a a 10-item scale specifically designed to assess distress in population surveys. This scale evaluates the individuals on anxio-depressive symptoms over the last 30 days and provides a total score as an index of distress. The Functional Assessment of Chronic Illness Therapy (FACIT) Measurement System [38] is used for the management of chronic illness using questionnaires related to health-related quality of life. Its generic version known as the Functional Assessment of Cancer Therapy-General (FACT-G) is compiled to use in four primary quality of life domains including physical well-being, social/family well-being, emotional well-being, and functional well-being. A six-item sub-scale of Somatic and Psychological Health Report (SPHERE-12) measures the aspects of distress and related conditions [51]. This scale is based on GHQ [37] and each item is scored on a three-point scale between 0 and 2, which gives a maximum score of 12.

A number of scales for depression are also used to scale distress. Hospital Anxiety and Depression Scale (HADS) is a screening instrument that is used to assess anxiety and depression of physically ill patients [42]. It includes 14 items for anxiety and depression with 4 alternative answers, which are used to measure total distress score. Self-report scales including Beck's Depression Inventory (BDI) [41], and Patient Health Questionnaire - Anxiety and Depression Scale (PHQ-ADS) [52] have also been shown to have some relevance with distress for particular patient groups.

IV. Automatic Distress Assessment

Distress is highly prevalent in patients with chronic diseases. Despite the fact that it can cause serious harm, clinicians are reluctant to use the existing distress screening for various reasons, most importantly for the extensive time requirement. Automating the screening can greatly alleviate the problem by

TABLE I
DISTRESS SCALES

Scale	Symptoms	Number of Items	Required Time (minutes)
BSI [36]	Psychological distress	18/53	3–7
GHQ-12 [37]	Psychological disorders	12	3–7
FACT-G [38]	Quality of life	21	< 15
Mccorkle et al. [39]	Distress	10	—
SCL-90 [40]	Psychiatric disorders	90	>20
BDI [41]	Depression	21	5–10
HADS [42]	Depression/Anxiety	14	2-5
PHQ-9 [43]	Depression	9	<5

saving time of the diagnosis at the busy oncology practices. Based on the preliminary assessment through the automated systems, referral can be made to the psychologist for complete checkup. Due to the benefit researchers have started focusing on automating the distress screening. We discuss the related methodologies in this section.

Besides the application in health, automated distress detection has also been studied in two other areas: Aged Care and Forensic. In elderly homes distress calls include call for help if there is fall, fire etc. In the forensic scenario automated distress can potentially help the Police prioritise the crime response based on the intensity of distress of the caller. Also, automated distress detection can greatly assist the forensic phoneticians by providing them an objective measure of distress of victims in recorded attacks. In this section, we also discuss the methodologies used in these two sectors.

A. Health

For automated distress detection in health, most of the studies focused on distress related conditions such as depression, anxiety, PTSD, and suicidal behaviour; very few studies [53], [54] have reported their results on distress detection. For instance, an automated distress management system [55] is piloted in outpatient medical oncology practice using tablet or computer for tailored psychosocial coping recommendations or referrals to individuals after immediate analysis. The authors used Distress Thermometer and problem list proposed by National Comprehensive Cancer Network as a screening tool. The designed system matches patients identified concerns with the problem list and proposes evidence-based treatment suggestions and referrals. Verona coding definitions of emotional sequences (VR-CoDES) was developed for the detection and categorisation of patients' emotions and their corresponding healthcare physicians [56]. Different studies have exploited VR-CoDES [57]–[59], however, the need for training of researchers on its usage and required labour for labelling consultation recording are its major practical limitations. In this regard, Birkett et al. [60] developed computer-based tools to assist VR-CoDES in the labelling of patients-physicians' recordings. The authors tried different representations of patients utterances and evaluated well-known classifiers including naïve Bayes, logistic regressions, support vector machines, and boosted ensemble decision trees for the labelling of recordings as an explicit concern, an emotional cue, or neither.

Researchers are predominantly attempting to infer distress based on the after effect such as depression, anxiety, PTSD, and suicidality, have developed various techniques. In [61], authors analysed 33 individuals from a clinical trial of depression [62] and investigated the relationship between nonverbal behaviour and severity of depression using video recording over the course of treatment. Scherer at al. [63] evaluated different visual features for psychological disorder analysis. They found that depressed individuals tend to gaze downwards more, give less intense and shorter duration of smile, and show longer self-touches and fidgeting. The inclusion of gender information with the visual is found to be helpful in detecting of distress related situations [64]. In addition to the visual indicators, Space-Time Interest Points (STIP) features are also exploited to detect depression with significantly improved results [65], [66]. These features include gestures related to head, face, shoulder, hands movements.

Recent studies have shown the promise of using speech as an effective marker for diagnosis and monitoring of depression. Speech can provide a wide range of prosodic, spectral, and formant features associated with depression. Many researchers have used speech as an objective indicator for the detection of depression [67]–[69]. An interactive voice response (IVR) system was used to collect speech samples for automated HAM-D measures of depression severity [70]–[73]. Acoustic features such as spectral, prosodic, cepstral, glottal, and features obtained from Teager energy operators (TEO) were investigated for clinical depression detection in adolescents [74]. TEO based features were produced more promising results compared to all other features and their combinations. Other studies [75]–[78] also investigated different acoustic features and identified more relevant identifier for depression. Ozdas et al. [79] studied excitation related speech parameters including glottal flow spectrum and vocal jitter for identification of major depressed, high-risk near-term suicidal, and non-suicidal patients. Vocal jitter was found a significant discriminator clue suicidal and non-depressed control, where glottal flow spectrum related parameters provided discrimination of all three groups with significantly improved results. Scherer et al. [69] used prosody and voice quality related speech parameters for identification of suicidal and non-suicidal adolescents. They found that suicidal adolescents tend to have more breathy voice qualities compared to non-suicidal. A comparative study performed in [80] using acoustic and prosodic features to detect depression in spontaneous speech. Authors found that voice features such as intensity, root mean square, and loudness performed best to detect depression in the dataset. Other studies (for example [81]–[85]) also exploited different machine learning techniques and suggested that the speech can be effectively utilised to detect distress and related conditions.

B. Aged Care

Life expectancy is increasing globally, leading us to a higher number of older people in our society [86]. This increasing share of the elderly population is changing the cause of death from infectious and parasitic illnesses to chronic non-communicable diseases [87], [88]. Ageing can lead to physical limitations that need to be compensated by technical assistance or with the help of aged care services. In aged care homes community, the feeling of isolation, fear, and a sense of helplessness cause distress. Older people in residential care are also prone to the risk of distress due to physical limitations to do routine tasks.

Distress in elderly often goes unrecognised due to different reasons: confusing or unknown symptoms of distress [10], avoidance from checkups [89], and lack of systematic method or tool for distress detection [90]. The early detection and treatment of distress among elderly are very important because it can enhance recovery from illness [10]. There are different innovative products or solutions which intend to promote independence and better quality of life among seniors with physical or cognitive diseases. For instance, CIRDO project [91] aims to automatically detect the situations of falls and distress in residential care to promote autonomy for elderly people. This system involves video and audio analysis to detect the risky situation and make necessary emergency call using e-lio system[1] For distress detection, they evaluated the proposed system using Automatic Speech Recognition (ASR) to detect distress sentences in AS80 [92] corpus and achieved promising results. SweetHome project [93] used home equipped noise robust multisource automatic speech recognition (ASR) to detect vocal command or distress sentences in the realistic noisy environment of a smart home. 23 speakers, including 9 women, were participated in this experiment, and closest distance between speakers and microphone was 2 meters. They performed voice order recognition of speech command belonging to three classes: distress calls, neutral sentences, and home automation orders. Sound based surveillance system is presented in [94] to detect alarming sounds in home situation. This system performed real-time audio analysis for the detection of distress situation without compromising patients' privacy.

Distress detection in elders using ASR system is a very challenging task due age-related degeneration of vocal cords, problems of laryngeal cartilages, and changes in larynx muscles [95], [96]. Some studies have empirically shown that ASR models performed poorly on elderly voice when they are trained on young or middle-aged adult speech [97], [98]. For such situations, speaker adaptation techniques or training ASR model on elderly voice can help improvement in recognition rate [99]. To explore the performance of ASR in distress situation, Aman et al. [92] presented word error rate in aged voice compared to non-aged speech. They showed that ASR system gives higher word error rate equal to equal to 43.5% for the aged group and 9% on young speakers.

C. Forensic

Distress detection has an increasing presence in forensics. It provides opinions about the authenticity of distress in criminal investigations. In forensic investigation, the lie can occur from distortion, denial, evasion, concealment, and outright fabrication by people to appear non-accountable for their exertions [100]. Distress detection systems are used to find the presence of reliable emotional clues to detect malingering. Forensic examinations are performed by psychologists using different techniques including interviews, observations, home or institutional visits, psychological tests, instruments, as well as other methods recognised by the council [101]. Automatic distress detection can play a crucial role in the assisting the forensic examination practice with an objective measure that can assist the judicial authorities.

A comprehensive study was performed by Lisa [102] to investigate distress speech using acoustic and perceptual cues and empirically compare the results for real-life victims and actors in life-threatening situations. Based on the results of the acoustic analysis, it is concluded that acoustic parameters can be utilised to detect distress situations for actors and victims. In another study, Lisa [103] reported that two acoustic parameters intensity and formant bandwidth are helpful in differentiating between acted and genuine victims' speech. Similarly, F0 mean, range and vowel formant can be used to distinguish between baseline and distress conditions for both victims and actors.

V. Distress Datasets

Development of automated systems require historical data that contains the correlation of physical properties such as speech, facial expressions with distress labels. In this section we discuss various datasets that have been used previously for the purpose of distress identification. Notably as depression is a possible after effect of distress most of these datasets are built to diagnose depression. We conclude this section summarising the sector wise studies (health, age care, and forensic) with the datasets used within, in Table II.

A. Distress Assessment Interview Corpus (DAIC)

The Distress Analysis Interview Corpus (DAIC) [168] includes semi-structured clinical interviews of participants to enable the diagnosis of psychological distress conditions such as depression, anxiety, and post traumatic stress disorder. The interviews of participants were conducted by humans, human controlled agents and autonomous agents. Overall data consists of audio, video, and questionnaire responses of participants and each interview is labelled with a depression score using PHQ-9. A portion of this dataset was released in Audio/Visual Emotion Recognition Depression Sub-challenge (AVEC) [169] 2016, which also contains transcription of the interviews.

[1]http://www.technosens.fr/.

TABLE II
STUDIES ON AUTOMATED DISTRESS DETECTION IN DIFFERENT SETTINGS.

Scope	**Corpus**	**Scale**	**Modality**	**Method**	**Focus**	**References**
Aged Care	AD80	Distressed Sentences	Speech	Speech to Text using ASR	Distress Situation Detection	[91], [92], [104]–[108]
	French Adapted Speech Corpus					[109]–[115]
	CIRDO Corpus					[105], [113], [116]
Forensic	Self Generated by Author	Distressed/non-distressed speech	Speech	Acoustic Analysis	Distressed/non-distressed speech detection	[102], [103]
Healthcare	Distress Analysis Interview Corpus (DAIC)	PCL-C, PHQ-9	Audio, Video	Verbal/Non-verbal/Fusion Analysis	Depression and PTSD	[69], [117], [118]
		PHQ-9			Depression	[119]–[121]
		STAI, PHQ-9, PCL-C			**Distress**	[63], [122]
	Virtual Human Distress Assessment Interview Corpus (VH DAIC)	PHQ-9, PCL-C	Audio, Video	Verbal/Non-verbal/Fusion Analysis	Depression, and PTSD	[64], [123], [124]
	Distress Analysis Interview Corpus-Wizard of Oz (DAIC-WOZ)	PHQ-8	Audio, Video, Text	Verbal/Non-verbal/Text/ Fusion Analysis	Depression	[125]–[136]
	Audio-Visual Depressive Language (AViD) Corpus, AVEC 2014 Audio-Visual Depression Corpus (AVEC)	BDI-II	Audio, Video	Verbal/Non-verbal/ Fusion Analysis	Depression	[137]–[147] [148] [85] [65], [149], [150] [136]
	Black Dog	DSM-IV, HAM-D	Audio, Video	Verbal/Non-verbal/Fusion Analysis	Depression	[66], [151]–[157]
	Pittsburgh	DSM-IV, HAM-D	Audio, Video	Verbal/Non-verbal/Fusion Analysis	Depression	[61], [158]–[165] [62]
	ORYGEN	Conventional diagnostic tests	Audio, Video	Verbal/Non-verbal/Fusion Analysis	Depression	[166], [167]

B. *Aged and Non-Aged Corpus (AS80)*

This corpus was recorded for adaptation of standard Automatic Speech Recognition (ASR) system to aged voice [92]. This corpus contains recording of from 95 speakers who were asked to read distress and casual sentences. These sentences contain a list of home automation orders and of distress calls that could be uttered by an elderly person in distress or fall situations.

C. *AVEC Corpus 2013*

This dataset contains 340 video recordings of subjects performing a Human-Computer Interaction tasks [148]. There were total 292 speakers and the length of each recorded video clip is between 20 to 50 minutes. The level of depression for recordings was labelled using Beck Depression Inventory (BDI-II) [170]. The AVEC corpus 2014 [171] is a portion of this dataset which contains 300 video with the duration from 6 seconds to 4 minutes.

D. *SDC (suicidal, depressed, and control subjects)*

This database is the collection of different dataset. Suicidal corpus was collected from the existing datasets [172] that was recorded from phone conversations, treatment sessions, and suicide notes. Depression related samples were obtained from Vanderbilt II and depression dataset used by Hollon et al [173]. DSM-IV and, ICD-9-CM (International Classification of Diseases, ninth edition, Clinical Modification) criteria were used for depressed patients. For the control group sample, Vanderbilt II dataset was used.

E. *Pitt Depression Dataset*

This is a clinically validated depression dataset collected during the treatment of depressed patients at University of Pittsburgh (Pitt) [174]. All participants from a clinical trial were met with DSM-IV criteria for major depression. Total 57 patients were accessed using the HRSD clinical interview for depression severity. Interviews were recorded in audio-video format and depression was evaluated by the clinicians.

F. *Black Dog dataset*

This audio-visual dataset was recorded by the Black Dog Institute Australia [175]. Over 40 depressed individuals (both male and female) were interviewed and asked to read sentences. Audio-video recordings of subjects include self-directed speech, related facial expressions, and body language.

G. *Cincinnati Children's Interview Corpus (CCIC)*

This dataset [69] includes the interview of 60 children patients (average age 15.47 years) at the Emergency Department of Cincinnati Children's Hospital Medical Center. These children came to the hospital due to suicidal ideation, gestures, and attempts. Data was collected by a professional social worker. Due to lengthy interviews of suicidal and non-suicidal patients, only 60 seconds of speech for each participant is utilised for the analysis [176].

VI. DISCUSSIONS

Distress is a complex condition that can potentially lead to depression, anxiety, sadness, suicide and other forms of psychological morbidity. The search of the literature found most of the papers related to distress are in the health area and focus was mostly on post-distress conditions including depression, anxiety, and Post Traumatic Stress Disorder (PTSD) to determine the presence of distress. It is evident from Table II where we present the summary of 75 studies on distress and related conditions in different settings (aged care, forensic, and healthcare), wherein the focus was mostly on depression and PTSD. These studies have statistically analysed depression, anxiety, and PTSD against distress and reported that distress is highly correlated with these measuring dimensions [177]–[179]. We found only two studies in Table II, [63], [122] that attempted to detect general distress automatically. However, these studies also statistically correlated depression, anxiety, and PTSD to categorise (high, low, unclear) distress. Note that this current approach to determining distress is debatable, as [180] reports, patients with distress may not have depression when measured with the BDI scale. **So, an independent distress screening technique is crucial.** Note that this is feasible as studies especially in Forensic [103] and Health [56] have shown that speech independently carries latent properties for inferring distress.

Currently, a number of distress screening tools are available, but as we report in Table I, most of these tools have many questions and require a considerable amount of time to complete. More importantly, it has been found that screening patients with multiple scales can appreciably improve the accuracy of results compared to single scale [181]. However, such multi-scale approach will further increase the screening time. Due to busy practices, oncologists are already reluctant to use distress screening tools, so a further increase in screen time will not be welcome by the oncology practices. Moreover, for aged care, and forensic scenarios, real-time distress inference is sought, so the time taking screening techniques will not be very useful. **An automated distress detection/screening is therefore inevitable.**

Datasets will play a vital role to develop an independent and automated distress detection system. From Section V, we found that most of the available datasets are recorded for depression, anxiety, and assessment of suicidal behaviour. Very few datasets such as AD80 is designed for distress in the elderly population. However, AD80 only focuses on the detection of distressed sentences using Automated Speech Recognition that focus on words ("help") spoken by individuals. In addition, each dataset has been recorded in different environment and validated using different scales, which is hard to use for developing the automated distress detection tool. **Therefore, it is crucial to develop large-scale validated datasets for automated detection of distress.**

REFERENCES

[1] B. A. Dachew, T. A. Bisetegn, and R. B. Gebremariam, "Prevalence of mental distress and associated factors among undergraduate students of university of gondar, northwest ethiopia: a cross-sectional institutional based study," Plos one, vol. 10, no. 3, p. e0119464, 2015.

[2] J. C. Enticott, E. Lin, F. Shawyer, G. Russell, B. Inder, S. Patten, and G. Meadows, "Prevalence of psychological distress: How do australia and canada compare?" Australian & New Zealand Journal of Psychiatry, vol. 52, no. 3, pp. 227–238, 2018.

[3] M. Benzeval and K. Judge, "Income and health: the time dimension," Social science & medicine, vol. 52, no. 9, pp. 1371–1390, 2001.

[4] C. R. Chittleborough, H. Winefield, T. K. Gill, C. Koster, and A. W. Taylor, "Age differences in associations between psychological distress and chronic conditions," International journal of public health, vol. 56, no. 1, pp. 71–80, 2011.

[5] A. Marchand, A. Demers, and P. Durand, "Do occupation and work conditions really matter? a longitudinal analysis of psychological distress experiences among canadian workers," Sociology of health & illness, vol. 27, no. 5, pp. 602–627, 2005.

[6] A. Drapeau, A. Marchand, and D. Beaulieu-Prévost, "Epidemiology of psychological distress," in Mental illnesses-understanding, prediction and control. InTech, 2012.

[7] A. I. Lazzarino, M. Hamer, E. Stamatakis, and A. Steptoe, "The combined association of psychological distress and socioeconomic status with all-cause mortality: a national cohort study," JAMA internal medicine, vol. 173, no. 1, pp. 22–27, 2013.

[8] ——, "Low socioeconomic status and psychological distress as synergistic predictors of mortality from stroke and coronary heart disease," Psychosomatic medicine, vol. 75, no. 3, p. 311, 2013.

[9] K. J. McLachlan and C. R. Gale, "The effects of psychological distress and its interaction with socioeconomic position on risk of developing four chronic diseases," Journal of psychosomatic research, vol. 109, pp. 79–85, 2018.

[10] P. Shivakumar, S. Sadanand, S. Bharath, N. Girish, M. Varghese et al., "Identifying psychological distress in elderly seeking health care," Indian journal of public health, vol. 59, no. 1, p. 18, 2015.

[11] R. F. Hanson, G. K. Sawyer, A. M. Begle, and G. S. Hubel, "The impact of crime victimization on quality of life," Journal of Traumatic Stress: Official Publication of The International Society for Traumatic Stress Studies, vol. 23, no. 2, pp. 189–197, 2010.

[12] J. A. Chiles, M. J. Lambert, and A. L. Hatch, "The impact of psychological interventions on medical cost offset: A meta-analytic review," Clinical Psychology: Science and Practice, vol. 6, no. 2, pp. 204–220, 1999.

[13] A. K. Otto, E. C. Soriano, S. D. Siegel, S. T. LoSavio, and J.-P. Laurenceau, "Assessing the relationship between fear of cancer recurrence and health care utilization in early-stage breast cancer survivors," Journal of Cancer Survivorship, vol. 12, no. 6, pp. 775–785, 2018.

[14] K. Hermelink, H. Höhn, S. Hasmüller, J. Gallwas, K. Härtl, R. Würstlein, and J. Köhm, "Brief distress screening in clinical practice: does it help to effectively allocate psycho-oncological support to female cancer inpatients?" Breast Care, vol. 9, no. 2, pp. 129–129, 2014.

[15] D. McLeod, M. J. Esplen, J. Wong, T. F. Hack, L. Fillion, D. Howell, M. Fitch, and J. Dufresne, "Enhancing clinical practice in the management of distress: The therapeutic practices for distress management (tpdm) project," Psycho-Oncology, vol. 27, no. 9, pp. 2289–2295, 2018.

[16] L. E. Carlson, A. Waller, and A. J. Mitchell, "Screening for distress and unmet needs in patients with cancer: review and recommendations," Journal of Clinical Oncology, vol. 30, no. 11, pp. 1160–1177, 2012.

[17] K. Hoffmann, M. Kamp, H.-J. Steiger, M. Sabel, and M. Rapp, "Correlation of psychooncological distress-screening and quality of life assessment in neurosurgical patients," Oncotarget, vol. 8, no. 67, p. 111396, 2017.

[18] L. J. Kirmayer, "Cultural variations in the response to psychiatric disorders and emotional distress," Social Science & Medicine, vol. 29, no. 3, pp. 327–339, 1989.

[19] A. Pampouchidou, P. Simos, K. Marias, F. Meriaudeau, F. Yang, M. Pediaditis, and M. Tsiknakis, "Automatic assessment of depression based on visual cues: A systematic review," IEEE Transactions on Affective Computing, 2017.

[20] N. Cummins, S. Scherer, J. Krajewski, S. Schnieder, J. Epps, and T. F. Quatieri, "A review of depression and suicide risk assessment using speech analysis," Speech Communication, vol. 71, pp. 10–49, 2015.

[21] M. Morales, S. Scherer, and R. Levitan, "A cross-modal review of indicators for depression detection systems," in Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology—From Linguistic Signal to Clinical Reality, 2017, pp. 1–12.

[22] L. E. Carlson and B. D. Bultz, "Cancer distress screening: needs, models, and methods," Journal of psychosomatic research, vol. 55, no. 5, pp. 403–409, 2003.

[23] N. C. C. Network et al., "Distress management. clinical practice guidelines." Journal of the National Comprehensive Cancer Network: JNCCN, vol. 1, no. 3, p. 344, 2003.

[24] A. I. for Preventive Medicine, "Common symptoms of distress? access date: 22-June-2018," https://healthylife.com/online/stress/StateOfMichigan/symptoms-of-distress.html.

[25] C. Darwin and P. Prodger, The expression of the emotions in man and animals. Oxford University Press, USA, 1998.

[26] P. Ekman, "An argument for basic emotions," Cognition & emotion, vol. 6, no. 3-4, pp. 169–200, 1992.

[27] ——, "Universals and cultural differences in facial expressions of emotion." in Nebraska symposium on motivation. University of Nebraska Press, 1971.

[28] C. for Clinical Interventions, "Understanding distress intolerance," https://www.cci.health.wa.gov.au/.

[29] G. C. Davey, "Disgust: the disease-avoidance emotion and its dysfunctions," Philosophical Transactions of the Royal Society B: Biological Sciences, 2011.

[30] T. negative emotion typology tool, "Distress," https://emotiontypology.com/typology/list/distress.

[31] C. on Recognition, N. R. Council et al., "Stress and distress: Definitions," 2008.

[32] C. D. Spielberger, "Stress, emotions and health." 1987.

[33] E. Carstens and G. P. Moberg, "Recognizing pain and distress in laboratory animals," Ilar Journal, vol. 41, no. 2, pp. 62–71, 2000.

[34] L. Fisher, M. M. Skaff, J. T. Mullan, P. Arean, D. Mohr, U. Masharani, R. Glasgow, and G. Laurencin, "Clinical depression versus distress among patients with type 2 diabetes: not just a question of semantics," Diabetes care, vol. 30, no. 3, pp. 542–548, 2007.

[35] W. H. Polonsky, L. Fisher, J. Earles, R. J. Dudl, J. Lees, J. Mullan, and R. A. Jackson, "Assessing psychosocial distress in diabetes: development of the diabetes distress scale," Diabetes care, vol. 28, no. 3, pp. 626–631, 2005.

[36] L. R. Derogatis and N. Melisaratos, "The brief symptom inventory: an introductory report," Psychological medicine, vol. 13, no. 3, pp. 595–605, 1983.

[37] D. P. Goldberg, R. Gater, N. Sartorius, T. B. Ustun, M. Piccinelli, O. Gureje, and C. Rutter, "The validity of two versions of the ghq in the who study of mental illness in general health care," Psychological medicine, vol. 27, no. 1, pp. 191–197, 1997.

[38] K. Webster, D. Cella, and K. Yost, "The f unctional a ssessment of c hronic i llness t herapy (facit) measurement system: properties, applications, and interpretation," Health and quality of life outcomes, vol. 1, no. 1, p. 79, 2003.

[39] R. McCorkle and K. Young, "Development of a symptom distress scale," Cancer nursing, vol. 1, no. 5, pp. 373–378, 1978.

[40] L. R. Derogatis, "Symptom checklist-90-revised (scl-90-r)," Lyndhurst, NJ: NCS Pearson, 1979.

[41] P. Olaya-Contreras, T. Persson, and J. Styf, "Comparison between the beck depression inventory and psychiatric evaluation of distress in patients on long-term sick leave due to chronic musculoskeletal pain," Journal of multidisciplinary healthcare, vol. 3, p. 161, 2010.

[42] A. S. Zigmond and R. P. Snaith, "The hospital anxiety and depression scale," Acta psychiatrica scandinavica, vol. 67, no. 6, pp. 361–370, 1983.

[43] L. S. Williams, E. J. Brizendine, L. Plue, T. Bakas, W. Tu, H. Hendrie, and K. Kroenke, "Performance of the phq-9 as a screening tool for depression after stroke," stroke, vol. 36, no. 3, pp. 635–638, 2005.

[44] J. Holland, M. Watson, and J. Dunn, "The ipos new international standard of quality cancer care: integrating the psychosocial domain into routine care," Psycho-oncology, vol. 20, no. 7, pp. 677–680, 2011.

[45] C. Regnard, J. Reynolds, B. Watson, D. Matthews, L. Gibson, and C. Clarke, "Understanding distress in people with severe communication difficulties: developing and assessing the disability distress assessment tool (disdat)," Journal of Intellectual Disability Research, vol. 51, no. 4, pp. 277–292, 2007.

[46] A. J. Roth, A. B. Kornblith, L. Batel-Copel, E. Peabody, H. I. Scher, and J. C. Holland, "Rapid screening for psychologic distress in men with prostate carcinoma: a pilot study," Cancer: Interdisciplinary International Journal of the American Cancer Society, vol. 82, no. 10, pp. 1904–1908, 1998.

[47] J. R. Zabora, R. Smith-Wilson, J. H. Fetting, and J. P. Enterline, "An efficient method for psychosocial screening of cancer patients," Psychosomatics, vol. 31, no. 2, pp. 192–196, 1990.

[48] K. Kosidou, A. Lundin, G. Lewis, P. Fredlund, H. Dal, and C. Dalman, "Trends in levels of self-reported psychological distress among individuals who seek psychiatric services over eight years: a comparison between age groups in three population surveys in stockholm county," BMC psychiatry, vol. 17, no. 1, p. 345, 2017.

[49] I. Cuéllar-Flores, M. P. Sánchez-López, R. M. Limiñana-Gras, and L. Colodro-Conde, "The ghq-12 for the assessment of psychological distress of family caregivers," Behavioral Medicine, vol. 40, no. 2, pp. 65–70, 2014.

[50] R. C. Kessler, G. Andrews, L. J. Colpe, E. Hiripi, D. K. Mroczek, S.-L. Normand, E. E. Walters, and A. M. Zaslavsky, "Short screening scales to monitor population prevalences and trends in non-specific psychological distress," Psychological medicine, vol. 32, no. 6, pp. 959–976, 2002.

[51] I. B. Hickie, T. A. Davenport, D. Hadzi-Pavlovic, A. Koschera, S. L. Naismith, E. M. Scott, and K. A. Wilhelm, "Development of a simple screening tool for common mental disorders in general practice." The Medical journal of Australia, vol. 175, pp. S10–7, 2001.

[52] J. Chilcot, J. L. Hudson, R. Moss-Morris, A. Carroll, D. Game, A. Simpson, and M. Hotopf, "Screening for psychological distress using the patient health questionnaire anxiety and depression scale (phq-ads): Initial validation of structural validity in dialysis patients," General hospital psychiatry, vol. 50, pp. 15–19, 2018.

[53] M. Pacula, T. Meltzer, M. Crystal, A. Srivastava, and B. Marx, "Automatic detection of psychological distress indicators and severity assessment in crisis hotline conversations." in ICASSP, 2014, pp. 4863–4867.

[54] S. Saleem, R. Prasad, S. Vitaladevuni, M. Pacula, M. Crystal, B. Marx, D. Sloan, J. Vasterling, and T. Speroff, "Automatic detection of psychological distress indicators and severity assessment from online forum posts," Proceedings of COLING 2012, pp. 2375–2388, 2012.

[55] V. B. Decker, G. S. Howard, H. Holdread, B. D. Decker, and R. M. Hamilton, "Piloting an automated distress management program in an oncology practice." Clinical journal of oncology nursing, vol. 20, no. 1, 2016.

[56] L. Del Piccolo, A. Finset, A. V. Mellblom, M. Figueiredo-Braga, L. Korsvold, Y. Zhou, C. Zimmermann, and G. Humphris, "Verona coding definitions of emotional sequences (vr-codes): conceptual framework and future directions," Patient education and counseling, 2017.

[57] L. Barracliffe, O. Arandjelovic, and G. Humphris, "Can machine learning predict healthcare professionals' responses to patient emotions," in Proc. International Conference on Bioinformatics and Computational Biology, 2017, pp. 101–106.

[58] L. Del Piccolo, H. De Haes, C. Heaven, J. Jansen, W. Verheul, J. Bensing, S. Bergvik, M. Deveugele, H. Eide, I. Fletcher et al., "Development of the verona coding definitions of emotional sequences to code health providers' responses (vr-codes-p) to patient cues and concerns," Patient education and counseling, vol. 82, no. 2, pp. 149–155, 2011.

[59] Y. Zhou, R. Black, R. Freeman, D. Herron, G. Humphris, R. Menzies, S. Quinn, L. Scott, and A. Waller, "Applying the verona coding definitions of emotional sequences (vr-codes) in the dental context involving patients with complex communication needs: An exploratory study," Patient education and counseling, vol. 97, no. 2, pp. 180–187, 2014.

[60] C. Birkett, O. Arandjelović, and G. Humphris, "Towards objective and reproducible study of patient-doctor interaction: Automatic text analysis based vr-codes annotation of consultation transcripts," in 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2017, pp. 2638–2641.

[61] J. M. Girard, J. F. Cohn, M. H. Mahoor, S. M. Mavadati, Z. Hammal, and D. P. Rosenwald, "Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses," Image and vision computing, vol. 32, no. 10, pp. 641–647, 2014.

[62] J. F. Cohn, T. S. Kruez, I. Matthews, Y. Yang, M. H. Nguyen, M. T. Padilla, F. Zhou, and F. De la Torre, "Detecting depression from facial actions and vocal prosody," in Affective Computing and Intelligent Interaction and Workshops, 2009. ACII 2009. 3rd International Conference on. IEEE, 2009, pp. 1–7.

[63] S. Scherer, G. Stratou, M. Mahmoud, J. Boberg, J. Gratch, A. Rizzo, and L.-P. Morency, "Automatic behavior descriptors for psychological disorder analysis," in Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on. IEEE, 2013, pp. 1–8.

[64] G. Stratou, S. Scherer, J. Gratch, and L.-P. Morency, "Automatic nonverbal behavior indicators of depression and ptsd: the effect of gender," Journal on Multimodal User Interfaces, vol. 9, no. 1, pp. 17–29, 2015.

[65] N. Cummins, J. Joshi, A. Dhall, V. Sethu, R. Goecke, and J. Epps, "Diagnosis of depression by behavioural signals: a multimodal approach," in Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge. ACM, 2013, pp. 11–20.

[66] J. Joshi, R. Goecke, G. Parker, and M. Breakspear, "Can body expressions contribute to automatic depression analysis?" in Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on. IEEE, 2013, pp. 1–7.

[67] N. Cummins, J. Epps, M. Breakspear, and R. Goecke, "An investigation of depressed speech detection: Features and normalization," in Twelfth Annual Conference of the International Speech Communication Association, 2011.

[68] N. Cummins, J. Epps, V. Sethu, and J. Krajewski, "Variability compensation in small data: Oversampled extraction of i-vectors for the classification of depressed speech," in Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on. IEEE, 2014, pp. 970–974.

[69] S. Scherer, G. Stratou, J. Gratch, and L.-P. Morency, "Investigating voice quality as a speaker-independent indicator of depression and ptsd." in Interspeech, 2013, pp. 847–851.

[70] K. A. Kobak, J. H. Greist, J. W. Jefferson, J. C. Mundt, and D. J. Katzelnick, "Computerized assessment of depression and anxiety over the telephone using interactive voice response." MD computing: computers in medical practice, vol. 16, no. 3, pp. 64–68, 1999.

[71] J. C. Mundt, K. A. Kobak, L. Taylor, J. M. Mantle, J. W. Jefferson, D. J. Katzelnick, and J. H. Greist, "Administration of the hamilton depression rating scale using interactive voice response technology." MD computing: computers in medical practice, vol. 15, no. 1, pp. 31–39, 1998.

[72] H. K. Moore, J. C. Mundt, J. G. Modell, H. E. Rodrigues, D. J. DeBrota, J. J. Jefferson, and J. H. Greist, "An examination of 26,168 hamilton depression rating scale scores administered via interactive voice response across 17 randomized clinical trials," Journal of clinical psychopharmacology, vol. 26, no. 3, pp. 321–324, 2006.

[73] J. C. Mundt, P. J. Snyder, M. S. Cannizzaro, K. Chappie, and D. S. Geralts, "Voice acoustic measures of depression severity and treatment response collected via interactive voice response (ivr) technology," Journal of neurolinguistics, vol. 20, no. 1, pp. 50–64, 2007.

[74] L.-S. A. Low, N. C. Maddage, M. Lech, L. B. Sheeber, and N. B. Allen, "Detection of clinical depression in adolescents' speech during family interactions," IEEE Transactions on Biomedical Engineering, vol. 58, no. 3, pp. 574–586, 2011.

[75] M. Alpert, E. R. Pouget, and R. R. Silva, "Reflections of depression in acoustic measures of the patient's speech," Journal of affective disorders, vol. 66, no. 1, pp. 59–69, 2001.

[76] J. K. Darby and H. Hollien, "Vocal and speech patterns of depressive patients," Folia Phoniatrica et Logopaedica, vol. 29, no. 4, pp. 279–291, 1977.

[77] D. J. France, R. G. Shiavi, S. Silverman, M. Silverman, and M. Wilkes, "Acoustical properties of speech as indicators of depression and suicidal risk," IEEE transactions on Biomedical Engineering, vol. 47, no. 7, pp. 829–837, 2000.

[78] E. Moore II, M. A. Clements, J. W. Peifer, and L. Weisser, "Critical analysis of the impact of glottal features in the classification of clinical depression in speech," IEEE transactions on biomedical engineering, vol. 55, no. 1, pp. 96–107, 2008.

[79] A. Ozdas, R. G. Shiavi, S. E. Silverman, M. K. Silverman, and D. M. Wilkes, "Investigation of vocal jitter and glottal flow spectrum as possible cues for depression and near-term suicidal risk," IEEE Transactions on Biomedical Engineering, vol. 51, no. 9, pp. 1530–1540, 2004.

[80] S. Alghowinem, R. Goecke, M. Wagner, J. Epps, T. Gedeon, M. Breakspear, and G. Parker, "A comparative study of different classifiers for detecting depression from spontaneous speech," in Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on. IEEE, 2013, pp. 8022–8026.

[81] J. Kandsberger, S. N. Rogers, Y. Zhou, and G. Humphris, "Using fundamental frequency of cancer survivors' speech to investigate emotional distress in out-patient visits," Patient education and counseling, vol. 99, no. 12, pp. 1971–1977, 2016.

[82] A. SALEKIN, J. W. EBERLE, J. J. GLENN, B. A. TEACHMAN, and J. A. STANKOVIC, "A weakly supervised learning framework for detecting social anxiety and depression," ACM Interactive, Mobile, Wearable, and Ubiquitous Technologies,, vol. 2, no. Article 1, 2018.

[83] P. Lopez-Otero, L. Docio-Fernandez, A. Abad, and C. Garcia-Mateo, "Depression detection using automatic transcriptions of de-identified speech," Proc. Interspeech 2017, pp. 3157–3161, 2017.

[84] S. Dham, A. Sharma, and A. Dhall, "Depression scale recognition from audio, visual and text analysis," arXiv preprint arXiv:1709.05865, 2017.

[85] S. Scherer, L.-P. Morency, J. Gratch, and J. Pestian, "Reduced vowel space is a robust indicator of psychological distress: A cross-corpus analysis," in Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on. IEEE, 2015, pp. 4789–4793.

[86] S. Latif, M. Y. Khan, A. Qayyum, J. Qadir, M. Usman, S. M. Ali, Q. H. Abbasi, and M. A. Imran, "Mobile technologies for managing non-communicable diseases in developing countries," in Mobile Applications and Solutions for Social Inclusion. IGI Global, 2018, pp. 261–287.

[87] S. Latif, J. Qadir, S. Farooq, and M. A. Imran, "How 5g wireless (and concomitant technologies) will revolutionize healthcare?" Future Internet, vol. 9, no. 4, p. 93, 2017.

[88] S. Latif, R. Rana, J. Qadir, M. Imran, S. Younis et al., "Mobile health in the developing world: Review of literature and lessons from a case study," IEEE Access, vol. 5, pp. 11 540–11 556, 2017.

[89] T. Davison, M. McCabe, D. Mellor et al., "Improving the detection and management of depression in aged care," InPsych: The Bulletin of the Australian Psychological Society Ltd, vol. 30, no. 6, p. 14, 2008.

[90] D. Clarke, L. McCall, G. Rowley et al., "A questionnaire to measure general practitioners' attitudes to their role in the management of patients with depression and anxiety," Australian family physician, vol. 31, no. 3, p. 299, 2002.

[91] S. Bouakaz, M. Vacher, M.-E. B. Chaumon, F. Aman, S. Bekkadja, F. Portet, E. Guillou, S. Rossato, E. Desserée, P. Traineau et al., "Cirdo: Smart companion for helping elderly to live at home for longer," Irbm, vol. 35, no. 2, pp. 100–108, 2014.

[92] F. Aman, M. Vacher, S. Rossato, and F. Portet, "Speech recognition of aged voice in the aal context: Detection of distress sentences," in Speech Technology and Human-Computer Dialogue (SpeD), 2013 7th Conference on. IEEE, 2013, pp. 1–8.

[93] M. Vacher, B. Lecouteux, and F. Portet, "Recognition of voice commands by multisource asr and noise cancellation in a smart home environment," in Signal Processing Conference (EUSIPCO), 2012 Proceedings of the 20th European. IEEE, 2012, pp. 1663–1667.

[94] D. Istrate, E. Castelli, M. Vacher, L. Besacier, and J.-F. Serignat, "Information extraction from sound for medical telemonitoring," IEEE Transactions on Information Technology in Biomedicine, vol. 10, no. 2, pp. 264–274, 2006.

[95] N. Takeda, G. R. Thomas, and C. L. Ludlow, "Aging effects on motor units in the human thyroarytenoid muscle," The Laryngoscope, vol. 110, no. 6, pp. 1018–1025, 2000.

[96] P. Mueller, "Acoustic and morphologic study of the senescent voice," Ear Nose Throat J, vol. 63, pp. 71–75, 1985.

[97] R. Vipperla, S. Renals, and J. Frankel, "Longitudinal study of asr performance on ageing voices," 2008.

[98] N. Vigouroux, P. Truillet, and R. Privat, "Etude de l¿ effet du vieillissement sur les productions langagières et sur les performances en reconnaissance automatique de la parole," Revue Parole, no. 31, pp. 281–318, 2004.

[99] A. Baba, S. Yoshizawa, M. Yamada, A. Lee, and K. Shikano, "Acoustic models of the elderly for large-vocabulary continuous speech recognition," Electronics and Communications in Japan (Part II: Electronics), vol. 87, no. 7, pp. 49–57, 2004.

[100] M. G. Frank and P. Ekman, "Nonverbal detection of deception in forensic contexts," in Handbook of forensic psychology. Elsevier, 2004, pp. 635–653.

[101] L. L. Gava and D. D. DellAglio, "Techniques used in forensic psychological examinations in cases of child and adolescent sexual abuse," Paidéia (Ribeirão Preto), vol. 23, no. 56, pp. 359–368, 2013.

[102] L. S. Roberts, "A forensic phonetic study of the vocal responses of individuals in distress," Ph.D. dissertation, University of York, 2012.

[103] L. Roberts, "Acoustic characteristics of distress speech in real victims and trained actors," in Presentation delivered to the 20th annual conference of the international association for forensic phonetics and acoustics, 24-28 July, 2011.

[104] F. Aman, M. Vacher, S. Rossato, and F. Portet, "In-home detection of distress calls: the case of aged users," in the 14rd Annual Conference of the International Speech Communication Association, INTERSPEECH, 2013, pp. 2065–2067.

[105] M. Vacher, B. Lecouteux, F. Aman, S. Rossato, and F. Portet, "Recognition of distress calls in distant speech setting: a preliminary experiment in a smart home," in Proceedings of SLPAT 2015: 6th Workshop on Speech and Language Processing for Assistive Technologies, 2015, pp. 124–129.

[106] F. Aman, V. Aubergé, and M. Vacher, "Influence of expressive speech on asr performances: application to elderly assistance in smart home," in International Conference on Text, Speech, and Dialogue. Springer, 2016, pp. 522–530.

[107] M. Vacher, F. Aman, S. Rossato, and F. Portet, "Development of automatic speech recognition techniques for elderly home support: Applications and challenges," in International Conference on Human Aspects of IT for the Aged Population. Springer, 2015, pp. 341–353.

[108] F. Aman, M. Vacher, S. Rossato, and F. Portet, "Analysing the performance of automatic speech recognition for ageing voice: Does it correlate with dependency level?" in 4th Workshop on Speech and Language Processing for Assistive Technologies, 2013, pp. 9–15.

[109] D. Istrate, M. Vacher, and J.-F. Serignat, "Embedded implementation of distress situation identification through sound analysis," The Journal on Information Technology in Healthcare, vol. 6, no. 3, pp. 204–211, 2008.

[110] M. Vacher, J.-F. Serignat, S. Chaillol, D. Istrate, and V. Popescu, "Speech and sound use in a remote monitoring system for health care,"

in International Conference on Text, Speech and Dialogue. Springer, 2006, pp. 711–718.

[111] A. Fleury, N. Noury, M. Vacher, H. Glasson, and J.-F. Seri, "Sound and speech detection and classification in a health smart home," in Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE. IEEE, 2008, pp. 4644–4647.

[112] M. Vacher, N. Guirand, J.-F. Serignat, A. Fleury, and N. Noury, "Speech recognition in a smart home: some experiments for telemonitoring," in Speech Technology and Human-Computer Dialogue, 2009. SpeD'09. Proceedings of the 5-th Conference on. IEEE, 2009, pp. 1–10.

[113] M. Vacher, S. Bouakaz, M.-E. Bobillier-Chaumon, F. Aman, R. A. Khan, S. Bekkadja, F. Portet, E. Guillou, S. Rossato, and B. Lecouteux, "The cirdo corpus: comprehensive audio/video database of domestic falls of elderly people," in 10th International Conference on Language Resources and Evaluation (LREC 2016). ELRA, 2016, pp. 1389–1396.

[114] M. Vacher, A. Fleury, F. Portet, J.-F. Serignat, and N. Noury, "Complete sound and speech recognition system for health smart homes: application to the recognition of activities of daily living," 2010.

[115] M. Vacher, F. Portet, A. Fleury, and N. Noury, "Challenges in the processing of audio channels for ambient assisted living," in e-Health Networking Applications and Services (Healthcom), 2010 12th IEEE International Conference on. IEEE, 2010, pp. 330–337.

[116] B. Lecouteux, M. Vacher, and F. Portet, "Distant speech processing for smart home: comparison of asr approaches in scattered microphone network for voice command," International Journal of Speech Technology, pp. 1–18, 2018.

[117] G. M. Lucas, J. Gratch, S. Scherer, J. Boberg, and G. Stratou, "Towards an affective interface for assessment of psychological distress," in Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on. IEEE, 2015, pp. 539–545.

[118] S. Scherer, G. M. Lucas, J. Gratch, A. S. Rizzo, and L.-P. Morency, "Self-reported symptoms of depression and ptsd are associated with reduced vowel space in screening interviews," IEEE Transactions on Affective Computing, no. 1, pp. 59–73, 2016.

[119] S. Scherer, G. Stratou, and L.-P. Morency, "Audiovisual behavior descriptors for depression assessment," in Proceedings of the 15th ACM on International conference on multimodal interaction. ACM, 2013, pp. 135–140.

[120] Z. Yu, S. Scherer, D. Devault, J. Gratch, G. Stratou, L.-P. Morency, and J. Cassell, "Multimodal prediction of psychological disorders: Learning verbal and nonverbal commonalities in adjacency pairs," in Semdial 2013 DialDam: Proceedings of the 17th Workshop on the Semantics and Pragmatics of Dialogue, 2013, pp. 160–169.

[121] B. Stasak, J. Epps, and N. Cummins, "Depression prediction via acoustic analysis of formulaic word fillers," Polar, vol. 77, no. 74, p. 230, 2016.

[122] S. Scherer, G. Stratou, G. Lucas, M. Mahmoud, J. Boberg, J. Gratch, L.-P. Morency et al., "Automatic audiovisual behavior descriptors for psychological disorder analysis," Image and Vision Computing, vol. 32, no. 10, pp. 648–658, 2014.

[123] G. Stratou, S. Scherer, J. Gratch, and L.-P. Morency, "Automatic nonverbal behavior indicators of depression and ptsd: Exploring gender differences," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 147–152.

[124] M. Chatterjee, G. Stratou, S. Scherer, and L.-P. Morency, "Context-based signal descriptors of heart-rate variability for anxiety assessment," in Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on. IEEE, 2014, pp. 3631–3635.

[125] L. Yang, D. Jiang, L. He, E. Pei, M. C. Oveneke, and H. Sahli, "Decision tree based depression classification from audio video and language information," in Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge. ACM, 2016, pp. 89–96.

[126] J. R. Williamson, E. Godoy, M. Cha, A. Schwarzentruber, P. Khorrami, Y. Gwon, H.-T. Kung, C. Dagli, and T. F. Quatieri, "Detecting depression using vocal, facial and semantic communication cues," in Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge. ACM, 2016, pp. 11–18.

[127] M. Nasir, A. Jati, P. G. Shivakumar, S. Nallan Chakravarthula, and P. Georgiou, "Multimodal and multiresolution depression detection from speech and facial landmark features," in Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge. ACM, 2016, pp. 43–50.

[128] A. Pampouchidou, O. Simantiraki, A. Fazlollahi, M. Pediaditis, D. Manousos, A. Roniotis, G. Giannakakis, F. Meriaudeau, P. Simos, K. Marias et al., "Depression assessment by fusing high and low level features from audio, video, and text," in Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge. ACM, 2016, pp. 27–34.

[129] B. Vlasenko, H. Sagha, N. Cummins, and B. W. Schuller, "Implementing gender-dependent vowel-level analysis for boosting speech-based depression recognition." in INTERSPEECH, 2017, pp. 3266–3270.

[130] N. Cummins, B. Vlasenko, H. Sagha, and B. Schuller, "Enhancing speech-based depression detection through gender dependent vowel-level formant features," in Conference on Artificial Intelligence in Medicine in Europe. Springer, 2017, pp. 209–214.

[131] L. Yang, D. Jiang, W. Han, and H. Sahli, "Dcnn and dnn based multi-modal depression recognition," in Affective Computing and Intelligent Interaction (ACII), 2017 Seventh International Conference on. IEEE, 2017, pp. 484–489.

[132] L. Yang, H. Sahli, X. Xia, E. Pei, M. C. Oveneke, and D. Jiang, "Hybrid depression classification and estimation from audio video and text information," in Proceedings of the 7th Annual Workshop on Audio/Visual Emotion Challenge. ACM, 2017, pp. 45–51.

[133] L. Yang, D. Jiang, X. Xia, E. Pei, M. C. Oveneke, and H. Sahli, "Multimodal measurement of depression using deep learning models," in Proceedings of the 7th Annual Workshop on Audio/Visual Emotion Challenge. ACM, 2017, pp. 53–59.

[134] M. Morales, S. Scherer, and R. Levitan, "A linguistically-informed fusion approach for multimodal depression detection," in Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic, 2018, pp. 13–24.

[135] S. Song, L. Shen, and M. Valstar, "Human behaviour-based automatic depression analysis using hand-crafted statistics and deep learned spectral features," in Automatic Face & Gesture Recognition (FG 2018), 2018 13th IEEE International Conference on. IEEE, 2018, pp. 158–165.

[136] B. Stasak, J. Epps, and R. Goecke, "An investigation of linguistic stress and articulatory vowel characteristics for automatic depression classification," Computer Speech & Language, vol. 53, pp. 140–155, 2019.

[137] M. Kächele, M. Glodek, D. Zharkov, S. Meudt, and F. Schwenker, "Fusion of audio-visual features using hierarchical classifier systems for the recognition of affective states and the state of depression," depression, vol. 1, no. 1, 2014.

[138] H. Meng, D. Huang, H. Wang, H. Yang, M. AI-Shuraifi, and Y. Wang, "Depression recognition based on dynamic facial and vocal expression features using partial least square regression," in Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge. ACM, 2013, pp. 21–30.

[139] A. Jan, H. Meng, Y. F. A. Gaus, F. Zhang, and S. Turabzadeh, "Automatic depression scale prediction using facial expression dynamics and regression," in Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge. ACM, 2014, pp. 73–80.

[140] Y. Zhu, Y. Shang, Z. Shao, and G. Guo, "Automated depression diagnosis based on deep networks to encode facial appearance and dynamics," IEEE Transactions on Affective Computing, 2017.

[141] R. Gupta and S. S. Narayanan, "Predicting affective dimensions based on self assessed depression severity." in Interspeech, 2016, pp. 1427–1431.

[142] X. Ma, D. Huang, Y. Wang, and Y. Wang, "Cost-sensitive two-stage depression prediction using dynamic visual clues," in Asian Conference on Computer Vision. Springer, 2016, pp. 338–351.

[143] J. R. Williamson, T. F. Quatieri, B. S. Helfer, R. Horwitz, B. Yu, and D. D. Mehta, "Vocal biomarkers of depression based on motor incoordination," in Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge. ACM, 2013, pp. 41–48.

[144] H. Meng and D. Huang, "Automatic emotional state detection using facial expression dynamic in videos," Smart Science, vol. 2, no. 4, pp. 202–208, 2014.

[145] M. Al Jazaery and G. Guo, "Video-based depression level analysis by encoding deep spatiotemporal features," IEEE Transactions on Affective Computing, 2018.

[146] X. Zhou, K. Jin, Y. Shang, and G. Guo, "Visually interpretable representation learning for depression recognition from facial images," IEEE Transactions on Affective Computing, 2018.

[147] A. Jan, H. Meng, Y. F. A. Gaus, and F. Zhang, "Artificial intelligent system for automatic depression level analysis through visual and vocal expressions," IEEE Transactions on Cognitive and Developmental Systems, 2017.

[148] M. Valstar, B. Schuller, K. Smith, F. Eyben, B. Jiang, S. Bilakhia, S. Schnieder, R. Cowie, and M. Pantic, "Avec 2013: the continuous audio/visual emotion and depression recognition challenge," in

Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge. ACM, 2013, pp. 3–10.
[149] H. Kaya, F. Eyben, A. A. Salah, and B. Schuller, "Cca based feature selection with application to continuous depression recognition from acoustic speech features," in Proceedings 39th IEEE International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2014, Florence, Italy, 2014.
[150] V. Mitra, E. Shriberg, M. McLaren, A. Kathol, C. Richey, D. Vergyri, and M. Graciarena, "The sri avec-2014 evaluation system," in Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge. ACM, 2014, pp. 93–101.
[151] J. Joshi, A. Dhall, R. Goecke, M. Breakspear, G. Parker et al., "Neural-net classification for spatio-temporal descriptor based depression analysis." in ICPR, 2012, pp. 2634–2638.
[152] J. Joshi, R. Goecke, S. Alghowinem, A. Dhall, M. Wagner, J. Epps, G. Parker, and M. Breakspear, "Multimodal assistive technologies for depression diagnosis and monitoring," Journal on Multimodal User Interfaces, vol. 7, no. 3, pp. 217–228, 2013.
[153] S. Alghowinem, R. Goecke, M. Wagner, G. Parker, and M. Breakspear, "Eye movement analysis for depression detection," in 2013 IEEE International Conference on Image Processing. IEEE, 2013, pp. 4220–4224.
[154] S. Alghowinem, R. Goecke, M. Wagner, G. Parkerx, and M. Breakspear, "Head pose and movement analysis as an indicator of depression," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 283–288.
[155] S. Alghowinem, R. Goecke, M. Wagner, J. Epps, M. Hyett, G. Parker, and M. Breakspear, "Multimodal depression detection: fusion analysis of paralinguistic, head pose and eye gaze behaviors," IEEE Transactions on Affective Computing, 2016.
[156] G. McIntyre, R. Göcke, M. Hyett, M. Green, and M. Breakspear, "An approach for automatically measuring facial activity in depressed subjects," in Affective Computing and Intelligent Interaction and Workshops, 2009. ACII 2009. 3rd International Conference on. IEEE, 2009, pp. 1–8.
[157] G. McIntyre, R. Goecke, M. Breakspear, and G. Parker, "Facial response to video content in depression," in MMCogEmS Workshop: Inferring Cognitive and Emotional States from Multimodal Measures, 13th International Conference on Multimodal Interaction ICMI2011, Alicante, Spain, 2011.
[158] H. Dibeklioğlu, Z. Hammal, and J. F. Cohn, "Dynamic multimodal measurement of depression severity using deep autoencoding," IEEE journal of biomedical and health informatics, vol. 22, no. 2, pp. 525–536, 2018.
[159] J. Joshi, "An automated framework for depression analysis," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 630–635.
[160] J. Joshi, A. Dhall, R. Goecke, and J. F. Cohn, "Relative body parts movement for automatic depression analysis," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 492–497.
[161] J. F. Cohn, "Social signal processing in depression," in Proceedings of the 2nd international workshop on Social signal processing. ACM, 2010, pp. 1–2.
[162] J. M. Girard, J. F. Cohn, M. H. Mahoor, S. Mavadati, and D. P. Rosenwald, "Social risk and depression: Evidence from manual and automatic facial expression analysis," in Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on. IEEE, 2013, pp. 1–8.
[163] J. F. Cohn, "Beyond group differences: specificity of nonverbal behavior and interpersonal communication to depression severity." in AVEC@ ACM Multimedia. Citeseer, 2013, pp. 1–2.
[164] S. Alghowinem, R. Goecke, J. F. Cohn, M. Wagner, G. Parker, and M. Breakspear, "Cross-cultural detection of depression from nonverbal behaviour," in Automatic Face and Gesture Recognition (FG), 2015 11th IEEE International Conference and Workshops on, vol. 1. IEEE, 2015, pp. 1–8.
[165] H. Dibeklioğlu, Z. Hammal, Y. Yang, and J. F. Cohn, "Multimodal detection of depression in clinical interviews," in Proceedings of the 2015 ACM on International Conference on Multimodal Interaction. ACM, 2015, pp. 307–310.
[166] K. E. B. Ooi, L.-S. A. Low, M. Lech, and N. Allen, "Prediction of clinical depression in adolescents using facial image analaysis," 2011.
[167] K. Ooi, "Early prediction of clinical depression in adolescents using single-channel and multi-channel classification approach," 2014.
[168] J. Gratch, R. Artstein, G. M. Lucas, G. Stratou, S. Scherer, A. Nazarian, R. Wood, J. Boberg, D. DeVault, S. Marsella et al., "The distress analysis interview corpus of human and computer interviews." in LREC. Citeseer, 2014, pp. 3123–3128.
[169] M. Valstar, J. Gratch, B. Schuller, F. Ringeval, D. Lalanne, M. Torres Torres, S. Scherer, G. Stratou, R. Cowie, and M. Pantic, "Avec 2016: Depression, mood, and emotion recognition workshop and challenge," in Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge. ACM, 2016, pp. 3–10.
[170] A. T. Beck, R. A. Steer, and G. K. Brown, "Beck depression inventory-ii," San Antonio, vol. 78, no. 2, pp. 490–498, 1996.
[171] M. Valstar, B. Schuller, K. Smith, T. Almaev, F. Eyben, J. Krajewski, R. Cowie, and M. Pantic, "Avec 2014: 3d dimensional affect and depression recognition challenge," in Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge. ACM, 2014, pp. 3–10.
[172] S. E. Silverman, M. K. Silverman et al., "Methods and apparatus for evaluating near-term suicidal risk using vocal parameters," Jun. 13 2006, uS Patent 7,062,443.
[173] S. D. Hollon, R. J. DeRubeis, M. D. Evans, M. J. Wiemer, M. J. Garvey, W. M. Grove, and V. B. Tuason, "Cognitive therapy and pharmacotherapy for depression: Singly and in combination," Archives of general psychiatry, vol. 49, no. 10, pp. 774–781, 1992.
[174] Y. Yang, C. Fairbairn, and J. F. Cohn, "Detecting depression severity from vocal prosody," IEEE Transactions on Affective Computing, vol. 4, no. 2, pp. 142–150, 2013.
[175] S. Alghowinem, R. Goecke, M. Wagner, J. Epps, M. Breakspear, G. Parker et al., "From joyous to clinically depressed: Mood detection using spontaneous speech." in FLAIRS Conference, 2012.
[176] V. Venek, S. Scherer, L.-P. Morency, A. Rizzo, and J. Pestian, "Adolescent suicidal risk assessment in clinician-patient interaction: A study of verbal and acoustic behaviors," in Spoken Language Technology Workshop (SLT), 2014 IEEE. IEEE, 2014, pp. 277–282.
[177] P. J. Bieling, M. M. Antony, and R. P. Swinson, "The state–trait anxiety inventory, trait version: structure and content re-examined," Behaviour research and therapy, vol. 36, no. 7-8, pp. 777–788, 1998.
[178] G. N. Marshall, T. L. Schell, and J. N. Miles, "All ptsd symptoms are highly associated with general distress: Ramifications for the dysphoria symptom cluster." Journal of Abnormal Psychology, vol. 119, no. 1, p. 126, 2010.
[179] P. A. Arbisi, M. E. Kaler, S. M. Kehle-Forbes, C. R. Erbes, M. A. Polusny, and P. Thuras, "The predictive validity of the ptsd checklist in a nonclinical sample of combat-exposed national guard troops." Psychological Assessment, vol. 24, no. 4, p. 1034, 2012.
[180] D. G. Tate, M. Forchheimer, N. Kirsch, F. Maynard, and A. Roller, "Prevalence and associated features of depression and psychological distress in polio survivors," Archives of physical medicine and rehabilitation, vol. 74, no. 10, pp. 1056–1060, 1993.
[181] K. Clover, G. L. Carter, A. Mackinnon, and C. Adams, "Is my patient suffering clinically significant emotional distress? demonstration of a probabilities approach to evaluating algorithms for screening for distress," Supportive Care in Cancer, vol. 17, no. 12, p. 1455, 2009.