# Using voice analysis as an early indicator of risk for depression in young adults

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Abstract—Increasingly frequent publications in the literature report voice quality differences between depressed patients and controls. Here, we examine the possibility of using voice analysis as an early warning signal for the development of emotion disturbances in young adults. As part of a major interdisciplinary European research project in four countries (ECoWeB), examining the effects of web-based prevention programs to reduce the risk for depression in young adults, we analyzed a large number of acoustic voice characteristics in vocal reports of emotions experienced by the participants on a specific day. We were able to identify a number of significant differences in acoustic cues, particularly with respect to the energy distribution in the voice spectrum, encouraging further research efforts to develop promising non-obtrusive risk indicators in the normal speaking voice. This is particularly important in the case of young adults who are less likely to exhibit standard risk factors for depression such as negative life experiences.

Index Terms—risk for depression, prevention, vocal parameters, acoustic analysis

# I. INTRODUCTION

Health professionals agree that the two most frequent types of mental illness worldwide are depression and generalized anxiety disorders, with evidence for strong co-morbidity [1], [2]. The incidence rates for these affective disorders have risen steadily, especially during and after the COVID pandemic. The segment of the population most affected are adolescents and young adults [3], [4]. Given that adolescence is a period of the life span in which rapid social, emotional, and cognitive development and major life transitions have to be faced, the risk for recurrent affective disorders may lead to major impairments in interpersonal, social, educational, and occupational functioning. Not surprisingly, health professionals give high priority to prevention and early intervention for depression and anxiety disorders in young people [5].

Consequently, a central task for research in this domain is the identification and assessment of the major risk factors for the development of these disorders as well as the elaboration of appropriate programs for prevention and early intervention. The literature shows convincing evidence for six major risk factors: widowhood, physical abuse during childhood, obesity, having 4–5 metabolic risk factors, sexual dysfunction, and job strain (as shown in a major umbrella review of 134 meta-analyses spanning 1283 studies; [6]). In addition, stable personality traits, such as neuroticism [7] and negative versus positive trait affect [8] are considered as major risk factors for affective disorders.

As it is difficult to prevent major life events or to change major personality dispositions and as adolescents are unlikely to have been frequently exposed to stressful life experiences such as widowhood or job strain, more promising targets for prevention and intervention programs for young adults need to be identified. One potential direction consists of identifying cognitive and emotional dysfunctions or vulnerabilities that may affect daily life. Research in this area has provided evidence for cognitive biases in attention, memory, interpretation of events, associations, and ideations that can be considered as increasing risk for emotional disturbances [9]. Specifically, it can be shown that appraisal biases, for example, unrealistic evaluation of one's control over events and coping with consequences of events, can create emotion dispositions (tendencies to frequently experience anxiety or sadness) which in turn may increase the risk for depression and anxiety disorder [10]-[12].

Cognitive biases and emotion dispositions can be identified before the potential onset of serious and recurrent episodes of depression or anxiety and are thus ideal candidates for early detection and intervention in order to prevent serious clinical consequences, especially in adolescents and young adults who may not yet have firmly established biases or vulnerabilities. While a large number of self-report instruments have been developed for several cognitive biases, it is desirable to complement these with more unobtrusive assessments of these risk factors. One particularly promising approach is the use of voice and speech indicators for depressive states.

This approach has a long history – see [13] for a review of the early developments and classic contributions. In recent years, research efforts have grown exponentially, partly due to the development of sophisticated software for acoustic analysis but also to an increased recognition of the clinical relevance of this approach (see [14], [15]). There are two major review articles on the research findings on the vocal-acoustic markers of affective disturbance, in particular depression: [16] systematically review the source, formant, spectral, and prosodic features that have been found to be linked to depressive states, and, in a very recent article, [17] review studies and highlight the effect of depression on speech production and bio-acoustic speech characteristics, suggesting that clinical depression diagnostics could be augmented by machine learning based speech processing. One potential indicator that is repeatedly reported in this literature is that voices of individuals suffering from depression tend to show relatively more energy in the lower frequency range of the spectrum compared to non-depressed individuals.

However, it is notable that there is a relatively large amount of inconsistency concerning the nature and direction of the findings as well as on the vocal-acoustic indicators in the findings for emotional disorders reported in this literature. One obvious reason is the complexity of the phenomena under investigation and the number of different factors involved. Thus, depression is a multi-faceted clinical category with components of anhedonia, hopelessness, helplessness, and other symptoms. And, while there is a high degree of comorbidity between depression and generalized anxiety disorders, [1], [2], there are some major differences with respect to the underlying symptomatology, with respect to agitation and arousal, that are likely to have differential effects on voice production. Another important factor contributing to differences in findings on vocal indices of emotional disturbances is the nature of the voice material collected (e.g., spontaneous vs. standard content, degree of ego-involvement, or duration of the speech samples).

Much of this work has been done with diagnosed cases of emotion disorders under clinical treatment in comparison to normal controls, making it extremely difficult to obtain comparable samples and control all pertinent variables. Furthermore, many results reported in this literature are not directly applicable to attempts at an early diagnosis of the risk of developing emotion disorders such as depression and generalized anxiety, especially in younger people. The current work explores the potential for the development of appropriate indicators and measurement options for the development of early detection and prevention measures in the case of risk for emotion disorders in adolescents and younger adults. The main aim is to identify which of a large number of standard acoustic voice variables show a significant relationship with the central criterion for the presence of a clinically significant risk level for depression – a score of  $\geq 10$  on the Public Health Questionnaire (PHO-8, [18]). In addition, on a more exploratory note, we examine whether specific emotion experiences reported by the participants for the current day are significantly related to specific acoustic voice features and whether this relationship is mediated by the clinical risk factor.

### II. METHOD

The data reported in this article have been collected as part of a major European Horizon 2020 project, Emotional Competence for Well-Being in Young Adults (ECoWeB; see Acknowledgement), consisting of web administration of appropriate diagnostic instruments and different types of prevention packages.

# A. Diagnostic instruments

To measure the risk for depression, the Public Health Questionnaire PHQ-8 [18] was used. Tendencies toward Generalized Anxiety Disorders were assessed with the GAD-7 [19]. In addition, the Warwick-Edinborough Well Being scale WEMWBS [20] was administered.

Emotion dispositions were assessed by a specially developed Monitor instrument. Users were asked to indicate which of 12 emotions they had experienced on the current day and with what intensity. They also had a choice of providing a detailed account of the most important experience on that day, either by a written text or a vocal recording of the specific situation experience. In addition, they were asked to indicate the specific emotions they had felt in this particular situation and rate the respective intensities.

# B. Voice recording

Data collection and intervention programs in ECoWeB were administered via phone app. In consequence, recording specifications (prompts, microphone, conditions, sampling rate) depended on the equipment used by the individual participant. Due to requirements formulated by the ethics committee of the project, the data needed to be anonymized before being sent from the user's device to the server for central storage. We used random splicing (RS) [21], [22], an algorithm that cuts the sample into segments and then re-assembles the segments in a randomized order. This method obfuscates especially the textual content of the samples and is well established to preserve acoustic features that correlate with emotional expression. The software has been made open source as part of the Nkululeko framework [23]. The RS method destroys dynamic acoustic aspects of speech. Nevertheless, we found that feature-based emotion detection is robust against RS (see details in the Supplemental Online Material).

## C. Acoustic analyses

We used two kinds of acoustic feature sets on the data: the Nkululeko software [23] and openSMILE eGeMAPS and features extracted by the Praat software. The openSMILE framework [24] extracts acoustic feature sets that are based on frame-based low level descriptors, such as F0 and combined by statistical functionals. We used the eGeMAPS set [25], an expert set of 88 acoustic features. These features work well with many speech classification tasks and have been used as a kind of standard acoustic features in the scientific community (about 1500 citations based on Google scholar). In addition, we extracted typical features with the Praat software [26] using the scripts by David Feinberg [27]. Both feature sets cover various voice quality characteristics (e.g., jitter, shimmer, harmonics to noise ratio, spectral slope), articulatory characteristics (e.g., formant frequencies), as well as prosodic characteristics (pitch, energy, speech rate).

TABLE I

Acoustic parameters with significant differences ( $p \le .05$ ) between low and high risk for depression groups (PHQ  $\ge 10$ ) in a multivariate Analysis of CoVariance (ANCOVA, controlling for GAD, WEMWBS, gender, and country of origin). Note: UV = unvoiced, V = voiced.

	Low_Risk mean	High_Risk mean	p	Partial $\eta^2$	Interpretation: high risk participants have:
F0 semitone mean	33.77	32.26	0.005	0.022	lower F0
mfcc2 mean	8.19	10.44	0.001	0.030	steeper falling slope, less vocal energy
mfcc4 mean	-2.85	-0.6	0.019	0.015	hard to interpret phonetically; possibly differences
					in lexical content
logRel F0-H1-H2 mean	7.38	6.16	0.033	0.013	normalized amplitude ratio of first two harmonics;
					more glottal constriction (creaky voice)
slope V0-500 mean	0.025	0.020	0.036	0.012	less rising slope up to F1, might indicate an
					overall steeper falling spectral slope
alphaRatio UV mean	-11.51	-12.00	0.021	0.015	less high frequency energy in fricatives
F0 Hz mean	195.76	183.91	0.004	0.023	lower F0

# D. Participants

363 participants from four European countries (Great Britain, Belgium, Germany, and Spain; 14.1% male, 84.0% female, 1.9% other; between 16-21 years of age) recorded a vocal description of a situation that had elicited an emotion.

165 participants recorded only one emotion experience, 198 participants recorded several situations at different days, yielding a total of 1102 voice records. In this case, for the statistical analyses, rated emotion intensities and acoustic parameters were averaged over the different situations reported by single participants.

# **III. RESULTS**

In order to determine which acoustic voice parameters show significant differences between participants with low and high risk categorization on the basis of their PHQ scores (cut-off level: > 10), we computed a multivariate Analysis of CoVariance (ANCOVA), including all acoustic parameters measured, controlling for the scores on the Generalized Anxiety questionnaire (GAD) and the Well Being Scale (WEMWBS) as well as for gender and country of origin. We used this covariance model to ensure that high and low risk for Depression scores were not affected by differential values for GAD and WEMWBS, given that the GAD is positively and the WEMWBS negatively correlated with PHQ, nor by gender or country differences. The results showing the acoustic parameters with significant differences for low vs. high risk are shown in Table I. We ensured that these parameters were not affected by random splicing (see details in the Supplemental Online Material).

These results shown in Table I suggest that the issue of spectral balance, the relationship between the vocal energy in the lower and upper frequency ranges, may provide information on the likelihood of the risk for emotional disturbance. The indicators listed in Table 1 can be subdivided into articulatory, voice quality, and prosodic markers for high depression risk.

a) Articulation: We find differences in alphaRatioUV mean, which in the eGeMAPS feature set is defined as the energy of high (1-5 kHz) to low (50-1000 Hz) energy in the spectrum in unvoiced segments. Lower values for high-risk participants can indicate a reduced energy of high frequency fricative noise, which can be due to a lesser degree of fricative constriction [28], [29]. Along these lines, high-risk

patients overall might show an articulatory undershoot [30] and overall less energetic speech expressed in a lower degree of articulatory constrictions.

*b)* Voice quality: We find differences in logRelF0-H1-H2 as well as in the spectral slope features mfcc2\_mean and slopeV0-500. LogRelF0-H1-H2 is defined as the amplitude ratio of the 1st and 2nd harmonic normalized by the amplitude of the 0th harmonic (i.e., the local spectral peak at the f0 frequency). SlopeV0-500 is the spectral slope in voiced segments between 0 and 500 Hz which is in the first formant's frequency region. Mfcc2\_mean denotes the arithmetic mean value of the 2nd mel frequency cepstral coefficient.

LogRelF0-H1-H2 has been shown to be a robust correlate for glottal constriction as given for example in creaky voice (see [31] for a review). Results in Table 1 show lower logRelF0-H1-H2 values indicating a stronger glottal constriction with potentially more creaky voice quality for the high depression risk participants. One might speculate that the increase in glottal constriction, which serves to protect the trachea, serves as a defense mechanism.

The spectral slope features mfcc2 and slopeV0-500 can be related to vocal effort differences. Generally, increased vocal effort is expressed in more abrupt glottal closures [32], which show acoustically in an energy boost towards higher frequency regions [33]–[35], see [36] for an overview. This higher frequency energy boost causes a flatter spectral slope. In line with [37] we observe higher mfcc2 values for the high depression risk group. [37] show that this difference reflects reduced energy in the frequency band from 2000 to 3000 Hz. They attribute their findings to vocal tract changes that are not further specified. Additionally to such potential articulatory changes, the reduced energy in this frequency band can be interpreted to express a steeper spectral downward slope and thus to indicate reduced vocal effort for the high depression risk group. The second slope feature SlopeVO-500 mean shows a less rising slope towards the first formant's energy peak for high depression risk participants. This again can be attributed to an overall steeper falling spectral slope. Thus, taken together our results indicate that the high-risk participants can be characterized by overall less vocal effort and a stronger glottal constriction.

c) Prosody: High-risk participants speak with a lower pitch level (F0semitone\_mean, meanF0Hz). This observation

#### TABLE II

Discriminant analysis of high vs. Low Risk for depression based on the variable set reaching significance in the ANCOVA shown in Table I. Note: Pooled within-groups correlations between discriminating variables and the standardized canonical discriminant function. Variables ordered by absolute size of correlation within function Classification 66.4% (cross-validated 63.9%) of original grouped cases correctly classified (Wilks Lambda 0.952, p < 0.015).

Structure Matrix	Function 1
mfcc4 mean	.576
mfcc2 mean	.558
logRelF0-H1-H2 mean	548
F0semitoneFrom mean	533
meanF0Hz	529
slopeV500-1500 mean	411
alphaRatioUV mean	229

confirms the findings of the majority of studies reviewed in [16]. The lower pitch level might amongst others be attributed to overall lower arousal (see e.g. [38]) of high risk participants.

Finally, mfcc4\_mean, the mean value of the fourth Mel frequency coefficient differs between the high and low risk groups which confirms the findings of [39], who observed a significant relation between this coefficient and the PHQ-9 score. This feature is harder to interpret in phonetic terms as it might indicate differences in the lexical content in the emotion reports of low and high risk participants that can be observed regardless of the spoken language.

In a second step, we ran a Discriminant analysis with the binary scale PHQ risk (high – low) as the dependent variable and the set of acoustic parameters yielding significant differences in the ANCOVA analysis described above, as predictors. Table II shows the structure matrix of the analysis. 66.4% (cross-validated 63.9%) of original grouped cases were correctly classified (Wilks lambda 0.952, p ; 0.015). This analysis confirms the role of spectral balance as a potential indicator of risk for depression, suggesting that a classification rate that is somewhat better than pure chance can be achieved.

As mentioned on the outset, we also wanted to explore the possibility of using vocal cues to identify emotion dispositions, which have been shown to play a role in the development of risk for depression. A major theoretical prediction on the origin of risk for depression is the assumption that an appraisal bias of low control/coping ability tends to produce an emotion disposition for experiencing frequently anxiety and sadness [11], [12]. Using an Emotion Monitor instrument, the participants in the current study reported on each assessment day with which intensity (from 0 to 7) they had experienced each 12 emotions, seven of which are considered as particularly relevant for depression risk: high anxiety, sadness, shame, and low amusement, joy, pleasure. A discriminant analysis on high/low risk with stepwise entry showed that high intensity of anxiety was the best predictor for risk (sig. of F to remove .044). To a lesser extent low intensity of joy also contributed (sig. of F to remove .063).

# IV. DISCUSSION

As a limitation there are unequal numbers of participants in the high and low risk group, which affects significance testing, but this is unavoidable as persons at risk will always constitute a smaller portion of an unselected sample. There is a biased gender distribution (84% female to 14% male), reflecting the overall bias in the ECoWeB study as a whole. Furthermore, participants in the study could choose whether to use the option to vocally report an emotion experience on each one of the several survey dates, but only a small percentage of the full sample did so.

# V. CONCLUSION

As outlined in the Results section we found articulatory, prosodic, as well as voice quality markers for high depression risk: Articulatory features indicate an articulatory undershoot and overall less energetic speech expressed in a lower degree of fricative constrictions. Prosodically, we mainly observe a lower pitch register related to lower arousal showed as an indicator for high depression risk. Voice quality markers suggest an overall reduction in vocal effort as well as a tighter glottal constriction. These findings confirm and elaborate earlier results on the important role of acoustic indicators of depressive disorder, particularly with respect to the importance of the mel frequency cepstral coefficient (mfcc) parameters.

Given that we found these significant effects in a study of potential risk factors with young adolescent participants not currently diagnosed with clinical depression but passing the established threshold for corresponding risk on an established diagnostic instrument, indicates the utility of investing in further research using voice analysis to determine risk factors for emotional disorders in a timely fashion. While it is unlikely that acoustic parameters alone can guarantee a valid diagnosis of risk for depression, they can be most valuable in addition to other behavioral indicators (such as facial expression, see [15] and self report indices such as appraisal bias and negative emotion dispositions [12].

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# VII. BIOGRAPHY SECTION



Klaus R. Scherer Klaus Scherer (Ph.D. Harvard University) has held professorships at the University of Pennsylvania and the Universities of Kiel, Giessen, and Geneva. He is currently an emeritus professor at the University of Geneva and an honorary professor at the University of Munich. His extensive work on different aspects of emotion, in particular vocal and facial expression and emotion induction by music, has been widely published in international peer-reviewed journals. Klaus Scherer is a fellow of several international scientific societies

and a member of several learned academies. He founded and directed the Swiss Center for Affective Sciences, held an Advanced Grant of the European Research Council and has been awarded honorary doctorates by the universities of Bologna, Bonn, and Fribourg.



**Björn W. Schuller** Björn W. Schuller received his diploma, doctoral degree, habilitation, and Adjunct Teaching Professor in Machine Intelligence and Signal Processing all in EE/IT from TUM in Munich/Germany where he is Full Professor and Chair of Health Informatics. He is also Full Professor and Artificial Intelligence and the Head of GLAM at Imperial College London/UK, co-founding CEO and current CSO of audEERING amongst other Professorships and Affiliations. Previous stays include Full Professor at the University of Augsburg/Germany

and University of Passau/Germany, Key Researcher at Joanneum Research in Graz/Austria, and the CNRS-LIMSI in Orsay/France. He is a Fellow of the ACM, Fellow of the IEEE and Golden Core Awardee of the IEEE Computer Society, Fellow of the BCS, Fellow of the ELLIS, Fellow of the ISCA, Fellow and President-Emeritus of the AAAC, and Elected Full Member Sigma Xi. He (co-)authored 1,500+ publications (60,000+ citations, h-index 115), is Field Chief Editor of Frontiers in Digital Health, Editor in Chief of AI Open and was Editor in Chief of the IEEE Transactions on Affective Computing amongst manifold further commitments and service to the community. His 50+ awards include having been honoured as one of 40 extraordinary scientists under the age of 40 by the WEF in 2015. Currently, he was awarded ACM Distinguished Speaker for the term 2024-2027 and IEEE Signal Processing Society Distinguished Lecturer 2024.



Felix Burkhardt Dr. Felix Burkhardt does teaching, consulting, research and development with respect to speech based emotional human-machine interfaces. Originally an expert of Speech Synthesis at the Technical University of Berlin, he wrote his ph.d. thesis on the simulation of emotional speech by machines, recorded the Berlin acted emotions database, "EmoDB", and maintains several open source projects, including the emotional speech synthesizer Emofilt, the speech labeling and annotation tool Speechalyzer and the machine learning platform

Nkululeko. Since 2018 he is the research director at audEERING after having worked for the Deutsche Telekom AG for 18 years. From 2019 to 2022 also was a full professor at the institute of communication science of the Technical University of Berlin.



**Uwe D. Reichel** Uwe D. Reichel is working as a senior researcher at audEERING GmbH and is also affiliated at the Hungarian Academy of Sciences. He received his master of science and his doctoral degree in Speech Science at the University of Munich in 2002 and 2010. The topic of his doctoral thesis was automatized intonation modelling and its linguistic interpretation. He worked as a research fellow at the Institute of Phonetics and Speech Processing, Munich, and as a Humboldt research fellow at the Institute for Linguistics at the Hungarian Academy

of Sciences in Budapest, the latter financed by a 2 years Feodor Lynen research grant by the Alexander von Humboldt foundation from 2015 till 2017. His work covers speech- and text-based modeling and feature engineering for various paralinguistic and digital health topics.



Florian Eyben Leading tech and innovation at audEERING to deliver world leading products for speech emotion recognition and Deep Learning based audio analysis. Did a PhD at TUM, Munich, Germany on Computational Paralinguistics; expert in deep learning, audio feature extraction, signal processing, project management and tech innovation; lead author of the openSMILE toolkit, co-author of the GPU accelerated LSTM-RNN training toolkit CuRRENNT.



Fig. 1. Cross dataset emotion prediction performances to assess the impact of random splicing of the the Emo-DB training set (emodb\_rs) on model performance.

# APPENDIX

Because the Random Splicing (RS) method destroys the dynamic contours of the speech samples, we need to check whether central acoustic parameters that correlate with the prediction of emotional speech are disrupted. To test this, we performed RS on a whole database, namely the Berlin Emo-DB [40]. This database contains speech sampled from 10 German actors portraying 6 emotion categories plus a neutral version. We then compared this version with the original database as well as four other international databases, namely a Polish database [41], the US-American Ravdess database [42], the Italian Emovo database [43] and the Danish emotion database [44]. All of these include samples with ground-truth labels for the emotional categories neutral, happy, angry and sad. We performed 36  $(6 \cdot 6)$  machine learning experiments with these, using each database once, in a cross database setting, as a test split, once as a training split, and once doing the mono-database experiment (using the own train and test splits). As acoustic features we used the same that are the basis of this paper's analysis: The eGeMAPS set [25], an expert set of 88 acoustic features and the Praat software [26] features, using the scripts by David Feinberg [27]. Both feature sets simply got concatenated. As a classifier we used the Support Vector Machine (SVM) algorithm implemented by the sklearn package with a misclassification cost of .1. We did no optimization, as we were interested only in the comparison between experiments. The results are shown in Figure 1. It shows that the RS version of Berlin Emo-DB performs as good (and in parts even better) as the original one.

Furthermore, we ensured, that the acoustic parameters with significant differences for low vs. high depression risk shown in Table I were not affected by random splicing, the following way: we extracted the parameters on the Emo-DB dataset [40] on the original as well as on the randomly spliced signals and measured the concordance correlation coefficient (CCC) between the two variants. We defined feature robustness in terms of a CCC higher than .95. All significant acoustic parameters reached a CCC of .99 or higher indicating that



Fig. 2. Correlation of mean f0 values calculated on original vs randomly spliced audio files. The robustness of this feature against random splicing is indicated by a high correlation along the diagonal.

they are not or only negligibly affected by random splicing. Figure 2 shows an example correlation plot for the robust f0 mean feature.