Investigating correlation between verbal interactions and perceived stress

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***Abstract*— While moderate exposure to stress at work can act as productivity booster, prolonged exposure not only decreases productivity, but it can also lead to an array of health related problems. Therefore, monitoring stress levels and more importantly correlated stressors, becomes prerequisite for a productive workforce. Considering that verbal interaction is an integral part of workplace environments, we report the results of our study that investigates correlation between perceived stress levels and verbal interaction. 28 workers were monitored over 6 weeks through their smartphones during their daily, real-world behaviour, capturing both verbal interaction and perceived stress levels. Results show that more than half of participants show correlation between perceived stress levels and verbal interaction, while this correlation is observed for over 90% of highly stressed participants.**

I. Introduction

Stress has been linked to a number of conditions that impact both health and wellbeing. Prolonged exposure to stressors has been shown to contribute to coronary heart disease and negatively impacts work productivity and emotional health [1]–[3].

Typical methods of measuring stress rely on clinical questionnaires and self-reports, while there is less work carried out in measuring factors that are correlated with changes in perceived stress levels. In this regard, mobile technologies can play a significant role in monitoring behaviour of subjects [4]–[7] due to the familiarity of users and the multimodal sensing capabilities of these devices. In this paper we specifically focus on understanding correlation between self-reported stress levels of subjects and their surrounding context at workplace. That is, we investigate whether there exist correlation between verbal interaction among colleagues and perceived stress levels. For the purpose of our study, we do not limit the definition of colleagues solely to members of the same organisation, but also include external individuals, such as clients or members of other organisations.

Although there have been studies that have investigated correlation between interaction of colleagues and their perceived stress levels, for example study on workplace bullying [8], there has been no study focused on investigating correlation between *verbal interaction* among colleagues and perceived stress levels. Measuring verbal interactions is important, since they are an integral part of working environments. Verbal interactions occur frequently [9] and affect, not only the subjects that are interacting but, due to sound diffusion, may also affect subjects nearby, especially in open floor offices. Despite the importance of verbal interactions, their effect on workers and specifically in relation to their perceived stress levels, has not been studied. Our study provides an initial investigation of correlation between perceived stress levels and detected verbal interactions. The results presented in this paper pertain to a study of 28 workers, monitored over 6 weeks through their smartphones during their daily, real-world behaviour. Each participant was provided with a smartphone that had our app installed designed to capture both: verbal interactions among colleagues and their perceived stress levels.

The results of our study show that a correlation between perceived stress levels and amount of verbal interaction can be observed for majority of highly stressed subjects.

II. Related Work

A number of authors [10]–[13] have investigated correlation between human behaviour and perceived stress at work. One of the conclusions is that there are behaviour differences before and during experience of stress, however these differences are particular for each individual. Authors of [14] propose to recognize the occurrence of stress at work by analysing the human voice captured through smartphones' microphones as it is observed that stress has influence on vocal parameters [15]. They distinguish stress events by developing a voice based model where the model is trained with the audio data collected from both stressed subjects and not stressed subjects. Another method of capturing presence of human voice is developed in [9], while speech analysis library is developed by authors of [16] for investigating affect, stress, and mental health by analysing the real-time audio on the mobile phone. However, in our work, we detect presence of human voice from smartphones, rather than performing an analysis on the voice and use the result of analysis to investigate correlation of verbal interaction and perceived stress levels.

III. Detection of Verbal Interactions and Data Collection

A. Detection of Verbal Interactions

In order to detect verbal interactions of people at work, we developed an app running on Android phones. The app was installed for all the participants and included access to the microphone. Our app continuously processed speech data picked up from the microphone but did not store any speech for obvious privacy reasons. The sounds from the microphone were processed directly on the phone and the

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main purpose of the app was to distinguish between human voice and other environmental sounds in order to detect the presence of other people nearby engaged in a conversation. The fact that the range of the microphone is limited to nearby sound only, ensured that only conversations in the vicinity of the participant are detected. We extracted two audio features to perform a robust voice activity detection; Pitch and Mel-MultiBand Spectral Entropy Signature (Mel-MBSES) [17]. Studies have related the pitch with the measurement of voice fundamental frequency F0 [18]. Since the fundamental frequency in human voice ranges from 40 Hz to 600 Hz [19], pitch can be used as a feature for detecting voice. In this paper, we obtain the pitch using autocorrelation. Specifically, we use the algorithm YIN proposed by [20] as it has shown to be more accurate, robust to noise, and energy efficient; salient qualities for implementation on mobile devices. The MEL-MBSES contains the amount of entropy for every frequency band. To calculate the MEL-MBSES, a Hann window [21] is applied to every frame, then the N-point FFT is computed. The resulting frequency frame is then split using a 8 band-pass filter in Mel Scale from 0Hz to 3500Hz. For every band the spectral entropy is determined using the following equation:

$$H = \ln(2\pi e) + \frac{1}{2}\ln(\sigma_{xx}\sigma_{yy} - \sigma_{xy}^2) \tag{1}$$

where σ_{xx} and σ_{yy} are the variances of the real and imaginary part, and σ_{xy} is the covariance between the real and the imaginary part of the FFT coefficients in the corresponding bands. With this process we obtain the *entropygram* that is similar to the spectrogram which computes the amount of energy in time and frequency; the *entropygram* gives the amount of information along the time for every band in the Mel scale. In order to classify as human voice, the processed audio had to satisfy two conditions: (i) the calculated pitch lies between the range of human voice, and (ii) the frame is detected as voice according to an evaluation of the MEL-MBSES coefficients in a previously trained Support Vector Machine (SVM) classifier [22]. We constructed the SVM model by providing examples of MEL-MBSES coefficients calculated on frames coming from 3 minutes of voiced data and 3 minutes of background data. The coefficients of the SVM model were obtained using the SMO linear algorithm.

The device audio sampling frequency is 44100Hz. We set a frame every 1024 samples from the incoming audio. Pitch and Mel-MBSES features are calculated for each frame. If both conditions are satisfied, then the frame is labelled as human voice. At least 7 frames of every 30 frames (approximate 0.7 seconds), must be detected as voice in order to indicate voice activity in that audio segment.

B. Data Collection

Each of the 28 participants (17 male and 11 female, age 37.46 ± 7.26 years) was provided with a smartphone, with our app installed and were monitored over a period of 6 weeks, from November 2013 to December 2013. The Institutions Ethical Review Board approved all experimental procedures involving human subjects. Participants worked in an open-floor office. They were informed that the goal of the study was to monitor behaviour activities relevant to stress. All participants consented to participate in the study and to have their data recorded. Participants were free to use the smartphone in any way they wanted, with no restrictions whatsoever placed upon the use. The app collected data of the verbal interactions of the participants through continuous processing of sound picked up from their smartphones' microphone. As our focus is to investigate the participants' behaviour during work, we limit the collection of verbal interaction records only for the duration they spend at work.

TABLE I

SELF-ASSESSMENT EVALUATION

Stress Questions	
What is your stress level?	
Mood Related Questions (POMS)	
Positive Affect Questions	**Negative Affect Questions**
How do you feel right now?	How do you feel right now?
Friendly Effective Energetic Cheerful	Angry Tense Anxious Sad

IV. SELF-REPORTED STRESS LEVEL AND VALIDATION

A. Self-Reported Stress Level

We used clinically validated questionnaires to capture subjective stress levels and mood states of the participants at work. The questionnaire was implemented on the smartphones of the participants and they were asked multiple times (in the morning at the beginning of the work, around noon, and before leaving workplace) to respond to a set of questions in order to record their perceived stress level and their affect. The questionnaire contained a stress related question to capture the perceived stress level and a set of questions to capture the mood of the subjects, derived from the POMS (Profile of Mood States) scale [23]. We divide the set of questions derived from POMS into two groups considering their affect on mood states: i) "Positive Affect (PA)" questions that reflect the extent to which a person feels enthusiastic, active, and alert at work, and ii) "Negative Affect (NA)" questions that reflect the subjective distress and unpleasant engagement that subsumes a variety of aversive mood states, including anger, fear, and nervousness [24]. Questions are listed in Table I and they are answered using a 5-point scale, where 1 indicates "very slightly or not at all" and 5 indicates "extremely".

B. Validation of Self-reports

1) The Need for Validation: Even though use of self-reports is a common methodology to establish the ground truth, this method exhibits a number of drawbacks related to recall bias, confusion, memory impairments, low levels of self-awareness, and influence of the current mood. All of these factors may undermine the reliability of self-reported data. As such we have investigated the relationship between

TABLE II

CORRELATION BETWEEN SELF-PERCEIVED STRESS LEVEL, POSITIVE AND NEGATIVE AFFECT ($p < 0.05$)

Subject ID	Correlation of Stress and NA	Correlation of Stress and PA	Subject ID	Correlation of Stress and NA	Correlation of Stress and PA
94532	0.6985398	-0.425286	57407	0.7306724	-0.430938
84616	0.7398827	-0.518951	95521	0.382699	-0.244251
95513	0.659912	-0.613226	95505	0.4148786	-0.279528
94433	0.8292346	-0.693351	96040	0.5083714	-0.431313
88187	0.8375666	-0.618896	89953	0.7649136	-0.334489
89532	0.7208425	-0.778539	94714	0.4764756	-0.254526
94441	0.7797977	-0.405293	87684	0.5252363	-0.621862
95646	0.8264134	-0.476082	88278	0.6531365	0.005093
14446	0.3900387	-0.231105	95216	0.6962238	-0.096669
96479	0.7951167	-0.174079	93401	0.7113349	-0.255613
94722	0.7422335	-0.009649	87676	0.7998684	-0.040498
94516	0.8278581	-0.436122	95448	0.9309402	0.0055788
94813	0.8187707	-0.649923	95596	0.721183	-0.400619
94615	0.2274597	-0.057132	95414	0.6427902	-0.641001

TABLE III

CORRELATION BETWEEN AMOUNT OF VERBAL INTERACTION AND SELF-REPORTED STRESS LEVEL FOR ALL PARTICIPANTS ($p < 0.005$)

Subject ID	**Correlation (*r*)**	**Subject ID**	**Correlation (*r*)**
94532	0.5563939	57407	-0.008856525
84616	0.3374859	95521	-0.03755634
95513	0.2935621	95505	-0.4990229
94433	0.205761	96040	-0.1380091
88187	0.2167277	89953	0.4077225
89532	0.1585889	94714	-0.327003
94441	0.321188	87684	-0.1441046
95646	0.1291016	88278	-0.2990065
14446	0.08572432	95216	0.06630906
96479	0.1343686	93401	0.1487379
94722	-0.06028413	87676	0.1035276
94516	0.137888	95448	0.1211673
94813	-0.1504368	95596	0.2944516
94615	-0.1169308	95414	-0.0645339

self-reported stress level and the mood of the subjects. We have used Pearson product-moment correlation coefficient r that measures the degree of linear dependence between two variables.

2) Correlation between self-reported stress level and mood: As shown in Table I, information about the experienced stress at work is asked through a single question while the mental status/mood of the participants is evaluated through two different categories (positive and negative affect) of questions that are able to quickly asses the transient, fluctuating feelings, and enduring affect states. The data collection app prompted participants three times per day to answer the questionnaire. From the response to the questionnaire, we have extracted three scores: (i) stress score, (ii) positive score, and (iii) negative score. The "stress score" is retrieved from the answer to the stress related question. The "positive score" is evaluated through the sum of the scores of the questions fall into category named "Positive Affect Questions" and the "negative score" is evaluated through the sum of the scores of the questions of "Negative Affect Questions" category from Table I. From these scores, we have calculated an average daily score for stress, positive and negative affect for each subject. We compute the Pearson's correlation coefficient for each participant between his/her average stress score per day and the average positive and negative scores.

Table II shows that there exists correlation between the mood and the perceived stress level of subjects. Negative correlation exists between the reported stress level and positive affect for most of the participants, while positive correlation exists between stress and negative affect. This result reflects the findings of the existing studies in psychology [25], [26] which state that positive state of mind is inversely correlated with increasing stress levels. Positive correlation provides an indication of the reliability of answers from the individuals to reflect their mental state.

V. EXPERIMENTAL RESULTS

A. Correlation between Verbal Interaction and Self-reported Stress

From the sound analysis on the phone we extract information about the average speaking length and total duration of voice activity (speaking segments) of a user per day. To investigate the correlation between the verbal interaction of the participants with their self-reported stress levels at work, we compute the Pearson's correlation coefficient between the daily verbal interaction duration and self-reported stress levels of all the participants (shown in Table III). From Table III it can be seen that a *significant* ($p < 0.005$) positive correlation exists between the self-reported stress levels and duration of verbal interaction for 60.71% of the subjects (17 out of 28).

However, we have also investigated the correlation between self-reported stress levels and duration of verbal interaction for highly stressed subjects only.

1) Analysis of highly stressed subjects: For this analysis, we have identified highly stressed subjects from all the participants based on their self-reported stress levels. We considered a highly stressed participant if their average stress level score was at least 4 (out 5) for at least 70% of the days of the monitoring period. This means that highly stressed subjects reported daily stress score of 4 for at least 32 days out of 45 days that were monitored

We then computed the Pearson's correlation coefficient between the daily duration of verbal interaction and self-reported stress levels of *highly stressed* subjects (shown in Table IV). The results in the Table IV show that when considering only highly stressed users, the correlation of these subjects with verbal interaction, increases to 91.67% (11 out of 12 highly stressed subjects), whereas this number was 60.71% for the entire sample. These results are in line with the clinical studies (based on questionnaires) on subjects with highly stressful professions, such as teachers, nurses, social workers and police force. For example work in [27], [28] has shown that highly stressful professions tend to be accompanied with higher verbal interactions, in comparison

TABLE IV

CORRELATION BETWEEN AMOUNT OF VERBAL INTERACTION AND SELF-PERCEIVED STRESS LEVEL FOR THE STRESSED SUBJECTS($p < 0.005$)

Subject ID	Correlation (r)	Subject ID	Correlation (r)
94532	0.5563939	94722	-0.06028413
84616	0.3374859	96479	0.1343686
94441	0.321188	94516	0.137888
95513	0.2935621	14446	0.08572432
88187	0.2167277	95646	0.1291016
94433	0.205761	89532	0.1585889

to the average of general population.

VI. CONCLUSION

The work presented in this paper has shown that in a real-world study, conducted within an open-floor workplace environment, there is a correlation between self-reported stress levels and amount of verbal interaction. While positive correlation is observed for around 60% of the individuals taking part in our study, when considering highly stressed individuals only, this number increases to over 91%. Considering that we have investigated correlation between verbal interaction and perceived stress levels, we cannot conclude on causality, however a number of qualitative studies has shown that environments where where verbal interactions occur more frequently, such as open-office plans, negatively affect perceived stress levels [27]–[30].

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