Does verbal interaction among colleagues affect perceived stress levels?

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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. Methodologies for measuring perceived stress levels, based on clinical questionnaires and self-reports have been developed, however there is less work done in measuring factors that influence perceived stress levels. Considering that verbal interaction is an integral part of workplace environments, we report result 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 verbal interaction is not correlated with perceived stress levels for the overall sample; however, highly stressed subjects show a strong positive correlation between perceived stress levels and verbal interaction.**

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, both in retrospective studies and prospective studies [1], [2]. On the other hand, an inverted U function [3] is observed between stress and productivity at work [4]. That is, moderate stress can be a positive force in everyday life, while excessive, chronic, and repeated exposure to stress negatively impacts work productivity and emotional health [5]. Another consequence of chronic stress is burnout [6] that emerges when employees are exposed to working environments with high demands and low resources. It is a unique type of stress syndrome, characterized by emotional exhaustion, depersonalization, and diminished personal accomplishment. Burnout can lead to depression, which, in turn, has been linked to a variety of other health conditions such as heart disease, stroke, obesity and eating disorders and diabetes [7].

Considering these issues, it is evident the importance of monitoring not only stress levels, but also understanding factors that contribute to changes in stress levels within workplace. While, typical methods of measuring stress rely on clinical questionnaires and self-reports, there is less work carried out in measuring factors that are correlated with changes in perceived stress levels.

In this regard, mobile technologies, specifically smartphones, can play an important role in understanding the correlation between self-reported stress and changes in the environment around the subjects. This is enabled through increasing capabilities of smartphones to the point where they can measure diverse aspects of subjects behaviour and their surrounding context. Smartphones are not only highly capable, but they also have pervasive presence in the developed world, making them ideal candidates to study behaviour and context of subjects in the real-world. The fact that smartphones are familiar devices, allows capturing natural behaviour of subjects and as a consequence minimising "observer effect" [8]. Unprecedented opportunities are enabling new applications across a wide variety of domains, including healthcare [9], social interaction analysis [10], [11], [12], human behaviour analysis [13], and transportation [14]. While, opportunities in this area are vast, 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 [15], 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 [16] 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, specifically in relation to their perceived stress levels, has not been studied. Our study provides an understanding 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, which was developed by our group. The purpose of the app was two fold:

i) detecting verbal interactions; which was done through continuous processing of sound picked up from the smartphones' microphone. The sound was processed through our classification algorithm, based on a Support Vector Machine (SVM) [17] classifier in order to automatically recognise human voice and discriminate it from other, non-human sounds (described in detail in Section III-A); and

ii) capturing perceived stress levels; which was done through implementation of a clinically-validated questionnaire [18] on the smartphone, where subjects were prompted three times a day to answer several questions in order to record their perceived stress level (described in detail in Section IV-A).

Using the smartphones microphone to detect human voice had two advantageous characteristics: i) smartphone's microphone is typically in close proximity to the subject and ii) it has limited sensing range; which, ensured that only the sounds generated in close proximity of the subject were picked up. As a consequence, only verbal interactions in the vicinity of the subject, were taken into consideration.

It should be noted that there was no speech recorded on the phone. Our classification algorithm (described in Section III-A) processed sound from the microphone in real-time, on-device and the output was a binary variable, indicating whether human speech was detected or not at each 30 second sound segment.

The results of our study show that there does not exist strong correlation between verbal interactions and perceived stress levels across all subjects. However, when considering only highly stressed subjects, strong correlation with verbal interaction becomes evident, indicating that presence of verbal interaction may be counterproductive for highly stressed workers. Results of this study can be used to inform workplace policies that regulate exposure to verbal interaction; such as open office plans for example, that inherently expose workers to higher levels of verbal interactions.

The rest of this paper is structured as follows: Section II covers a discussion on related works of this field. Description of the detection of verbal interaction and the data collection process is outlined in Section III. A brief discussion of the collection and validation of the self-reported data is found in Section IV. The experimental results are shown in Section V. Finally, Section VI summarizes the results.

II. Related Work

A number of authors [19], [20] 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. Another approach to assess stress, relies on analysis of audio, physical activity, and communication, collected during workday through smartphones; in addition to heart rate variability data [21]. This study has shown that the combined usage of all features, derived from smartphones and sensors data, to train the classifier has ensured higher accuracy in detecting stress events than the usage of either the set of features derived from the smartphones data or sensors data. Measuring the heart-rate variability to quantify stress levels is also proposed in [22], [23], [24] where the heart-rate data is collected from wearable sensors, prior to and during training as well as to predict the stress resistance. Particularly, [24] has addressed the challenge of inferring stress levels of participants in real time through continuous monitoring and collection of physiological measurements from body-worn sensors. Authors of [25] 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 [26]. 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. The reported accuracies are higher for the indoor scenario than for the outdoor scenario. Another method of capturing presence of human voice is developed in [16], while speech analysis library is developed by authors of [27] 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 Interaction and Data Collection

A. Detection of Verbal Interaction

In order to detect verbal interaction 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 sound. The sounds from the microphone were processed directly on the phone and the main purpose of the app was to distinguish between human voice and other environmental sounds. This was done to detect the presence of other people nearby that are carrying out a conversation. The fact that the range of the microphone is limited and it picks up nearby sound only, ensured that only conversations in the vicinity of the participant are detected. Our sound processing algorithm is able to classify human voice from other environmental sounds.

We extracted two audio features to perform a robust voice activity detection; Pitch and Mel-MultiBand Spectral Entropy Signature (Mel-MBSES) [28]. Studies have related the pitch with the measurement of voice fundamental frequency F0 [29]. Since the fundamental frequency in human voice can ranges from 40 Hz to 600 Hz [30], 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 [31] 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 [32] 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 should 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 [17]. The SVM is a widely used machine learning algorithm and is based in the concept of projecting a set of data to a high dimensional feature space where a optimal separating hyperplane exists to separate data from different classes by maximizing the margin between the hyperplane and the nearest points of any class. Given n training points of dimension d, coming from two different classes $y_i = -1 \ o \ +1$, i.e.:

$$\{x_i, y_i\} \ where \ i = 1...N, \ y \in \{-1, 1\}, \ x \in \mathbb{R}^D \tag{2}$$

The equation of the hyperplane separating the above training set can be defined as:

$$\vec{w} \cdot \vec{x} + b = 0 \tag{3}$$

where $\vec{w}$ is the vector normal to the hyperplane and $\frac{b}{\|\vec{w}\|}$ is the perpendicular distance from the hyperplane to the origin.

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. When evaluated, the SVM model returns +1 when the frame is considered to be voiced and -1 when the frame is considered to be background. The coefficients of the SVM model were obtained by using the SMO linear algorithm from WEKA [33].

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 voiced in order to indicate voice activity in that audio segment.

B. Collection of Data

Each of the 28 participants was provided with a smartphone, having our app installed and were monitored over a period of 6 weeks, from November 2013 to December 2013. Each participant was free to use the smartphone in any way they wanted, with no restrictions whatsoever placed upon the use. This 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. During the observation period, continuously collected data from the app running on the phones of the participants was uploaded daily to a server.

TABLE I. SELF-ASSESSMENT EVALUATION

Stress Questions	
What is your stress level?	
Mood Related Questions (POMS)	
Is this something you are good at?	Does it take you effort?
How did you sleep last night?	Would you rather do something else?
	What is your current activity level?
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) during a day 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. The set of questions for retrieving the mood of the participants at work is derived from the *POMS* (Profile of Mood States) [18] scale which is a psychological self-report measure for evaluating transient, distinct mood states within an individual. 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 [34]. 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: The significant advantage of self-reported data is that it provides respondents' own view directly. Moreover, this method can be useful in situations where observational data are not normally available. Though self-reported process is a common methodology in many research fields for data collection and establishing the ground truth, this method exhibits a number of drawbacks including 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 and the use of the inaccurate self-reported data may lead to a misleading conclusion.

Authors of [35] measure the impact of recall bias. This study shows that varying the recall periods produced different self-reported results. Moreover, the reliability of the self-reported data may be threatened by the desire of the participants to misreport their view or activity so as to portray their behaviour in a more positive or negative light.

The above discussion introduces the necessity to validate the self-reported data collected by our app before performing further analysis. As mentioned before, our collected self-report contains two categories of information of participants: (i) perceived stress level, and, (ii) mood. During the validation process, we investigate the relationship between the reported self-reported stress level and the mood of the person. Details about this validation process is found in the following subsections.

2) Analysis Method: In this paper, to measure the strength of association between different features, we have used the Pearson product-moment correlation coefficient (refers to as *"r"*) which is widely used in the sciences as a measure of the degree of linear dependence between two variables. For two random variable X and Y the equation for Pearson correlation (r) is as follows:

$$r = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (4)$$

$$= \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (5)$$

The correlation (value of r) can range from -1 to 1. A value of -1 indicates a perfect negative linear relationship between variables, a value of 0 indicates no linear relationship between variables, and a value of 1 indicates a perfect positive linear relationship between variables.

3) 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 that is integrated in the smartphones, requests the participants to describe their experience of stress and mood at work during three times per day. 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 (e.g., What is your stress level?). 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.

Since participants were asked three times per day to respond to the questionnaire, we usually have three records of perceived stress levels and mood for each participant per day. From these, we have evaluated average scores for stress, positive and negative affect of a person per day. The "average stress score" for a day is calculated through averaging of all reports of stress levels for that day. The "average positive score" for a day is calculated through averaging of all reports of positive scores for that day. In a similar way the "average negative score" for a day is calculated. 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. 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
94532	0.6985398	-0.4252858
84616	0.7398827	-0.5189507
95513	0.659912	-0.6132255
94433	0.8292346	-0.6933508
88187	0.8375666	-0.6188958
89532	0.7208425	-0.7785392
94441	0.7797977	-0.405293
95646	0.8264134	-0.4760821
14446	0.3900387	- 0.2311053
96479	0.7951167	-0.1740789
94722	0.7422335	-0.009648964
94516	0.8278581	-0.4361223
94813	0.8187707	-0.6499231
94615	0.2274597	-0.0571323
95414	0.6427902	-0.6410007
95596	0.721183	-0.4006191
95448	0.9309402	0.005578828
87676	0.7998684	-0.04049791
93401	0.7113349	-0.2556129
95216	0.6962238	-0.09666856
88278	0.6531365	0.005093
87684	0.5252363	-0.6218616
94714	0.4764756	-0.2545262
89953	0.7649136	-0.3344888
96040	0.5083714	-0.4313127
95505	0.4148786	-0.279528
95521	0.382699	-0.2442507
57407	0.7306724	-0.4309382

Table II shows that there exists an association between the mood and the perceived stress level of people at work. It is found that a negative correlation exists between the stress level and positive affect for most of the participants, while it can be seen that stress was positively correlated with negative affect. This result reflects the findings of the existing studies in psychology [36], [37] which describe that positive state of mind is inversely correlated with stress while negative state of mind increases the level of stress. These results provide an indication that questions were not answered in a mechanical manner by the subjects, but reflect the actual mental state of the subjects. As such, the self-reported scores are reliable reflection of the actual state of the subjects.

V. EXPERIMENTAL RESULTS

In this section, we perform the statistical analysis on the collected dataset to understand the correlation between verbal interaction among colleagues and their perceived stress. Subsequently, we discuss the observed results in light of existing literature in psychology.

A. Correlation between Verbal Interaction and Self-reported Stress

The verbal interaction records captured by our app contain the voice activity/communication of the participants. Due to privacy reason, the system does not record the voice content, instead, it only detects the voice activity through a voice detection algorithm (described in Section III-A). This algorithm is able to differentiate between speaking and non-speaking segments. From the verbal interaction records, we extract information about the average speaking length and total duration of voice activity (speaking segments) of a user per day.

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

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

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 *highly significant* ($p < 0.005$) positive correlation exists between the self-reported stress levels and duration of verbal interaction for 60% of the subjects (17 out of 28). While this result could be due to random chance, we have performed another analysis. For the second analysis, we have considered highly stressed subjects only, which we describe in the next section.

1) Analysis for highly stressed subjects only: For this analysis, we have identified highly stressed subjects from all the participants based on their self-reported stress levels. For this purpose, a *stress threshold* is used to differentiate highly stressed subjects.

The threshold is applied on the average value of the self-reported stress levels of participants per day during the observation window. As mentioned in sub-secton IV-A, each participant rated his/her stress level at time t during a day in a range of 1 to 5. Considering this, the *stress threshold* is defined as 4 referring that a participant is identified as *highly stressed* if his/her average stress level is higher than 4 out of 5 for at least 70% days during the observation window. This indicates that a stressed subject is observed *highly stressed* for at least 32 days during the total 45 observation days.

Then, we compute the Pearson's correlation coefficient between the daily duration of the engaged verbal interaction and self-reported stress levels of the distinguished *highly stressed* participants (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

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

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

to 91.67% (11 out of 12 *highly stressed* subjects), whereas this number was 60% for the entire sample. These results are in line with the clinical studies (based on questionnaires) carried out previously on subjects with highly stressful professions, such as teachers, nurses, social workers and police force. For example work in [38], [39] has shown that highly stressful professions tend to be accompanied with verbal interactions, in comparison to average of general population.

VI. CONCLUSION

In this paper, we have focused on understanding the factors that affect the stress level within workplace. Particularly, we have investigated the correlation between the verbal interaction among colleagues and their perceived stress levels at work. Our result indicates that the amount of verbal interaction among colleagues can be an indicator for experiencing stress at work. This work has also demonstrated the feasibility and effectiveness of using mobile technologies in investigating work related stress, such as, monitoring stress levels and correlating stressors. This study will serve to inform workplace policies regarding verbal interaction among colleagues, especially in an open office environment where the occurrences of verbal interactions among colleagues are very common and negatively affect perceived stress levels [40], [41].

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