Towards Using Situational Information to Detect an Individual's Perceived Stress Level

Svenja Neitzel*, Frank Englert*, Rahul Dwarakanath*, Katharina Schneider§, Kathrin Reinke§, Gisela Gerlach§, Christoph Rensing*, Doreen Boehnstedt*, Ruth Stock-Homburg§
Technische Universität Darmstadt, Germany
*Multimedia Communications Lab, firstname.lastname@kom.tu-darmstadt.de
§Department of Marketing & Human Resource Management, firstname.lastname@stock-homburg.de

***Abstract*—The advent of state-of-the-art telecommunication devices like smartphones has led to a considerable increase in the amount of electronic communication exchanged. While the improved availability increases personal flexibility—reducing rigidity in time and place of communication—it comes at a price. The 'anytime, anyplace'-accessibility, which has become the norm in today's (working) society, can cause adverse effects to an individual's mood and emotions, and especially raise the stress level. Consequently, in this paper, we discuss methods for measuring stress via mobile devices, analyzing their pros and cons. Subsequently, we analyze which situational information—comprising the prevailing context of the users and their usage of communication devices—is useful for the quantification of the psychological stress perceived by users. Based on a field study with 27 participants, we observe that, while longer working hours and higher number of appointments have a positive correlation with an increased stress level, there is no one-fits-all method for stress measurement. In turn, we take the first steps towards non-intrusive methods to identify stressful situations and thus, lay the foundation for future research on stress mitigation.**

***Index Terms*—Stress Recognition, Mobile Sensing, ICT Usage**

I. Introduction

The recent advancements in the field of information and communication technology (ICT) have brought about profound changes to the lifestyles in modern-day society. Especially in the work domain, these radical changes have led to improved flexibility, allowing knowledge workers to plan everyday life more efficiently [1], [2]. However, with the help of devices such as laptops, smartphones, and tablet computers, the boundaries between different life domains have become more and more permeable [3], [4]. This blurring of boundaries, especially between work and private lives, can bear significant disadvantages. Existing work in organizational behaviour associates the usage of ICT with increased work-life conflicts [1], resulting in increased stress levels [5], moodiness, irritability, or even burnout [6].

Stress has been cited to be one of the primary negative effects of ICT on an individual [4], [5], [7]. In our work, we tackle this issue with respect to ICT usage and in particular, we focus on understanding how situational information—comprising the user context and specific characteristics of ICT usage—can be used to detect the stress level of the users. Specifically, we attempt to understand the correlation of situational information with psychological stress of an individual. In effect, we analyze the correlation of different communication events and behavioral patterns throughout the course of a day with perceived psychological stress.

One major hurdle towards the measurement of stress is the difficulty in estimating/obtaining stress indicators continuously over a day in a real-life scenario. Smartphones may be a solution to this problem; modern smartphones are equipped with a broad set of sensors, such as GPS, microphones, accelerometers, etc. Together with measurements from wearable sensors (e.g., smart watches), these sensing facilities can be used to determine the users' context (e.g., locative information, user activity, etc.), monitor their ICT usage (e.g., call events, number of messages exchanged, etc.), and measure the correlation with psychological stress. In doing so, we can identify situations that are stressful to the users and possibly, provide them with appropriate feedback to overcome the same.

In this paper, we describe the results of an interdisciplinary research project on stress measurement involving computer scientists and researchers in organizational behavior. The overarching goal of our work is to identify appropriate methods and indicators to determine the situations that ICT users perceive as stressful. To this end, we:

1) investigate which devices and methods are acceptable by individuals for measuring physiological and behavioral stress indicators,
2) describe an approach to identify indicators of stress by matching the perceived stress level with situational information of the day, and
3) identify relevant indicators to infer perceived psychological stress of an individual with the help of a modern smartphone.

This paper is structured as follows: Section II introduces the concept of psychological stress and gives a brief description of methods for measuring physiological, psychological, and behavioral indicators of psychological stress. We also present the results of our investigation on acceptance towards intrusive methods for day-to-day stress indicator measurements, which lays the foundation for our non-intrusive approach. In Section III, we introduce our data acquisition app, called *StressMon*, to monitor the stress level and the situational information of users. This application was deployed in a field study to gather data for finding relevant stress indicators. The

978-1-5090-4338-5/17/$31.00 ©2017 IEEE

analysis of the gathered data and our findings are presented in Section IV. Finally, Section V concludes the paper by identifying remaining challenges and exposing our plans for future work.

II. Stress Measurement

According to Cohen et al. [8], psychological stress can be attributed to an individual's perception of, or response to, environmental events (*stressors*), when they surpass his or her *adaptive mental capacity*. Stressful events can have a significant influence on an individual's affective states (mood fluctuations, depression, etc.), their behavioral patterns (decreased sleep, increased smoking, etc.), as well as physical health conditions (dementia, anxiety, etc.). In contrast to psychological stressors, physiological stressors, such as cold/warm temperatures, injury, chronic illness, etc., put strain on an individual's body, primarily leading to physical consequences (diseases, headaches, low energy states, etc.). We primarily deal with psychological stressors in our work, focusing on its different stress indicators.

People's reactions to psychological stressors can be broadly classified into psychological, behavioral, and physiological reactions [9]. While psychological responses are often studied using self-assessment methods with respect to health complaints and decreased well-being, studies on behavioral reactions to stressors have focused on behavioral changes that accompany a stress reaction, such as sleep disturbances. Finally, studies on physiological stress reactions have commonly focused on the autonomic nervous system. Especially physiological stress indicators are attractive in research since they can be measured with high precision using sensors. Recently, there has also been progress in measuring behavioral stress indicators (e.g., human speech [10], [11]). However, such continuous measurement methods require wearing sensing devices throughout the measurement period, which is not reasonable in real-life settings. Modern smartphones can partially mitigate comfort issues but they instigate privacy concerns. To investigate the acceptance of continuously monitoring different physiological and behavioral stress indicators, we conducted a study with 48 participants. In this section, we provide a brief overview on the three types of stress indicators for psychological stress, and finally present the results of the acceptance study.

A. Psychological Responses (Self-Assessment)

The most naive approach to obtain information about perceived stress is to ask an individual directly. The main limitation of this approach is that it demands the individual's attention, which may annoy or disturb him or her in real-life situations, and requires strong incentives to obtain accurate feedback. Modern smartphones with touch screens and permanent Internet connectivity can be well suited to obtain self-reported stress responses because individuals can react quickly and from almost any location. By using context information and by triggering questionnaires in adequate situations, the willingness of individuals to submit feedback can be further increased, e.g., opportune moments depending on an individual's mood [12]. This type of smartphone-based self-assessment approach is widely used in stress related studies [13]–[16].

B. Behavioral Reactions

Psychological stressors bring about different types of behavioral reactions, most commonly observed in human speech [10], [11]. From a purely technical point of view, smartphones and their microphones are optimal for non-intrusive estimation of stress indicators in the human voice [17]. Using the smartphone's camera, it is also possible to detect stress from facial features [18]. Furthermore, mobility patterns [19], communication patterns [15], [19] and phone usage patterns [16] have been used to detect an individual's emotions and mood. Stress can also be estimated by monitoring sleep [13], [20]. Overall, by observing behavior, it may be possible to identify and recognize patterns caused by psychological stressors.

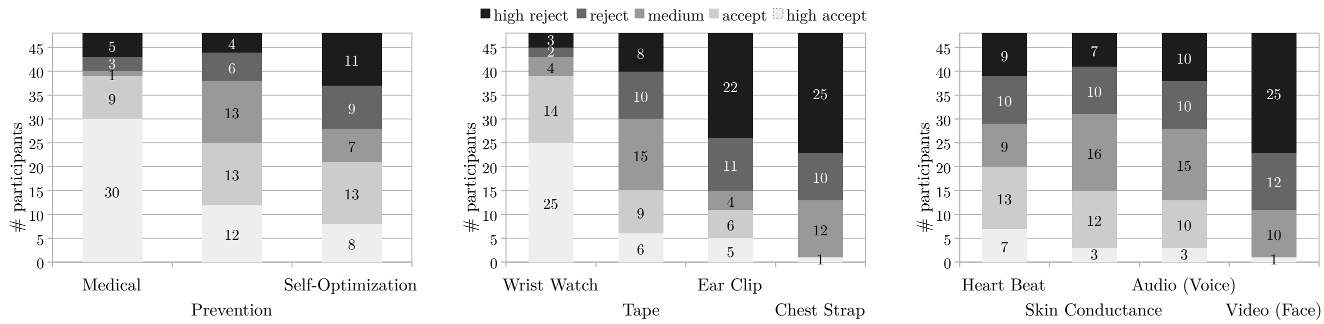
C. Physiological Reactions

Physiological reactions to stress are not specific to psychological stress, but can also be due to physical stressors that cause strain on an individual's body. Different physiological responses should be considered collectively in order to interpret an individual's psychological stress level [21]. *Cardiovascular activity* (heart rate, heart rate variability, etc.) has been studied quite extensively with respect to physiological stress reactions [22], [23]. Another important physiological stress response is *electrodermal activity* (e.g., skin conductivity level) [24]. State-of-the-art solutions to measure cardiovascular and electrodermal activities employ smartphones along with wearable sensors in wrist watches, chest straps, ear clips, and tapes [14], [16], [25], [26].

D. User Acceptance Study

In general, deploying stress measurement methods in real-life settings calls for a high level of user acceptance. According to the technology acceptance model [27], the acceptance is influenced by the perceived ease of use as well as the perceived usefulness of these methods. To investigate acceptance towards the continuous monitoring of different physiological and behavioral stress indicators, we conducted a study in form of a questionnaire. The study also dealt with the acceptance towards different sensor types and different motivations (i.e., medical, prevention, and self-optimization). The questionnaire was answered by 48 participants, who are mainly employees at two different universities in Germany and range from 24 to 57 years (*mean* = 31 years). As university employees might be more open towards new technologies, we expect the acceptance levels in this group to be slightly higher than in general.

Figure 1a shows that the acceptance towards the continuous monitoring of physiological parameters varies starkly across different motivations. Participants mainly comply with the monitoring of their physiological parameters for medical



(a) Acceptance towards different motivations (b) Acceptance towards different devices (c) Acceptance towards different sensor types

Fig. 1. Results of the user acceptance study on continuous monitoring of physiological and behavioral stress indicators.

reasons, i.e., for the purpose of diagnosis or special medical treatment. More than half of the participants accept the monitoring of physiological parameters for health prevention, i.e., early detection of unhealthy behavior. Most interestingly, around 40% of the participants reject the monitoring of physiological parameters for the purpose of self-optimization, i.e., optimizing own performance. The acceptance towards different wearable devices can be found in Figure 1b. The values indicate that wrist watches have a high acceptance by a wide margin. Tape gets the second rank but is only accepted by 33% of the participants. Ear clips and chest straps are highly rejected by a majority of the participants. Figure 1c shows that, irrespective of the type of sensor, the acceptance towards sensor-based stress measurement is rather low. Heart rate sensors achieve the highest acceptance, albeit by slightly more than 40% of the participants. Surprisingly, the acceptance towards skin conductance and voice sensors is very similar. In contrast, more than half of the participants highly reject the usage of face monitoring through camera sensors.

The survey results clearly show that participants are critical towards the continuous monitoring of stress-related physiological and behavioral parameters, and that the perceived usefulness of the monitoring plays an important role. We conclude that the use of cumbersome wearable sensors is not suitable for continuous stress measurement in real-life settings. Therefore, we propose a non-intrusive approach, in that we identify situational information that correlates with perceived stress, by exploiting the data obtainable on modern smartphones without any wearables. We estimate stress indicators by understanding the correlation between situational information and the corresponding perceived stress levels.

III. Data acquisition

Based on our findings in the acceptance study, we wanted to investigate whether we can detect psychological stress through situational information that can be easily obtained from modern smartphones. We implemented an Android smartphone app, called *StressMon*, to collect information on user context and ICT usage, together with the user's self-assessed stress level. The app requires no additional devices, and we set great value on a user-friendly interface and user guidance to maximize its comfortability and ease of use. Given the poor acceptance ratios of audio and video sensors in our study, we also refrained from using such potentially sensitive information to minimize privacy concerns. Apart from the self-assessed stress level—queried every evening on a five-point Likert scale ranging from one (not stressed) to five (stressed)—the intrusiveness of our app is as low as possible. When a user starts to use the app, we require him or her once to give the necessary permissions to our app. The user can actively teach the app special (i.e., private or occupational) contacts and locations, but our app also asks for contacts and locations that are likely to be special. For instance, if a user is present in a specific cell of the mobile network often and for a longer time, the app posts a notification in which the user immediately can tag the cell. The app further uses WiFi connections to find cells belonging to the same logical location in order to reduce the number of queries to the user. We implemented an incentive system in form of several badges so as to motivate the user to configure the app correctly, provide stress levels regularly and specify special contacts and locations.

In its current state, the app logs communication (calls with duration, received mails, received SMS, and received instant messages) together with the corresponding contact category (occupational/private), logical location (occupational/private), number and duration of appointments in the user's primary calendar, display events, usage of different app types, and the physical activity. All collected information is sent over WiFi to a secure server and stored in a database. The identity of the users is pseudonymized with their Android ID, a random number unique to each Android device, which is part of each database row. For privacy reasons, we do not store the usage of single apps but infer the type of the app directly on the user's phone. In order to categorize apps, we use a distributed approach. We offer a badge in our app for assigning one of eight predefined categories to some apps installed on the phone. The app names, together with their categories, are sent to the server, where all mappings are collected. In order to get an extensive and objective list of app-category pairs onto the single smartphones, the app regularly requests the current mappings from the server, which determines the final category for an app with a majority vote over all mappings. The user activity is obtained by using Google's activity recognition facilities [28]. However, we reduce the number of different actions, and thereby, the uncertainty for each action by matching actions to either *moving* (encompassing *in vehicle*, *on bicycle*, *walking*, and *running*) or *still*. Using screen (de-)activations, we infer other context information like the total time the user spends with the phone or the duration of sleep, which we approximate by the longest time the user does not activate the display from 8pm to 12 noon of the following day.

In order to make our app useful for users, we provide informative statistics about most of the collected parameters. In doing so, the users may monitor their ICT usage and other aspects of their way of living. Such self-reflection methods can be a first step to draw the users' attention to aspects of stress management and a responsible handling of ICT.

TABLE I
STRESS LEVEL DISTRIBUTION

stress level (numerical)	# stated	stress level (logical)	# stated
1	167	relaxed	167
2	144	normal	144
3 4 5	55 33 19	stressed	107

We conducted a field study from July 25 to August 21, 2016, where the app was used by 37 individuals, mainly employees working in four different companies. For the evaluation, we only used data from users who submitted at least seven stress levels over the whole run of the study. We also filtered out users who submitted less than two distinct stress levels. The final dataset for analysis includes data from 27 users, accounting for 418 stated stress levels in total. The users' age ranges from 26 to 57 years (*mean* = 44 years), with 75% being male. The lowest number of stated stress levels per user was 9 (stated by three users) and the highest was 24 (stated by one user), with a median of 15 stress levels per user. The distribution of stress levels can be found in Table I. Because higher stress levels (i.e., three, four and five) were stated much less frequent than lower stress levels (i.e., one and two), we decided to create three stress categories with similar size—*relaxed*, *normal* and *stressed*.

IV. DATA ANALYSIS

In this section, we analyze the correlations of the situational information collected by our app and the perceived stress level reported by the users during our study. Each stress level stated by a user in the evening of a day is assumed to correlate with the situational information collected over the course of that day (e.g., the total number of calls received that day). Because every user is assumed to have different habits and therefore, for instance, a different threshold for a low or high number of calls, all values are normalized per user. When a user has no differing values for single parameters (e.g., no calls for all days), we exclude him or her from the correlation analysis for the respective parameters. We calculate Pearson correlations in two different ways. First, we are interested in the correlation of the parameters with the perceived stress level over all of the users. A high correlation would indicate that the parameter influences the stress level for the majority of the users. However, since we have a different number of stress levels stated by each of the users, this overall correlation can be dominated by those users who submitted more stress levels than others. Therefore, we also calculated correlations per user and present the results in terms of percentiles.

The resulting correlations can be found in Table II. In terms of overall correlation, *number of appointments*, *duration of appointments*, and *duration of stay at work* are the highest positively correlated parameters with higher perceived stress ($r = 0.27$, $r = 0.23$ and $r = 0.20$, respectively). In contrast, *duration of stay at a private place* and *time spent with app categories 'news' and 'information'* are the highest negatively correlated parameters with higher perceived stress ($r = -0.21$, $r = -0.15$ and $r = -0.15$, respectively). For communication crossing the boundaries between different life domains, we observe that *private communication events at work* have a slightly positive correlation with higher perceived stress ($r = 0.14$). In contrast, we find no significant correlation between the *number of occupational communication events at a private place* with higher perceived stress.

Regarding correlations per user, we can say that *duration of stay at work* and *number of appointments* show a considerable positive correlation ($r \geq 0.29$ and $r \geq 0.27$, respectively) with higher perceived stress for 50% of the users. Moreover, 50% of the users show a negative correlation ($r \leq -0.27$ and $r \leq -0.17$, respectively) of *duration of stay at a private place* and *time spent with app category 'tools'* with higher perceived stress. Further, we observe highly differing correlations for different users. For instance, correlations for *duration of phone movement*, *duration of sleep*, *number of private communication events*, and *time spent with app categories 'communication' and 'office'* are roughly centered around zero and have a considerable ($|r| \geq 0.2$) negative as well as positive correlation for 25% of the users.

The collected situational information can be used to infer a user's stress level using machine learning techniques. Personalized models for each individual user are more accurate but require data collection for every user before predictions are possible. The amount of per-user data collected during our study is not enough to train and evaluate such personalized models. Instead, we can train a generalized model, which is less accurate but can provide predictions for new users much faster. For the purpose of demonstration, we train a simple NaiveBayes classifier on our dataset. As features, we select parameters that reached highly significant ($p \leq 0.01$) correlations in the correlation analysis. When two parameters passing this criterion are highly correlated with each other ($|r| \geq 0.3$), we remove the parameter with lower correlation from the feature set. The resulting features are *number of*

TABLE II
SITUATIONAL INFORMATION AND CORRELATION WITH PERCEIVED STRESS

Rank	Parameter (per day)	N		Correlation with higher stress level				
				Pearson (overall)		Pearson (per user)		
		# users	# stress levels	r	p	$p25$	$p50$	$p75$
1	Number of appointments	17	258	0.27	0.0000	-0.06	0.27	0.49
2	Duration of appointments	17	258	0.23	0.0002	-0.20	0.17	0.25
3	Duration of stay at a private place (minutes)	27	418	-0.21	0.0000	-0.36	-0.27	-0.01
4	Duration of stay at work (minutes)	20	326	0.20	0.0003	-0.06	0.29	0.49
5	Number of calls	27	418	0.18	0.0002	-0.10	0.13	0.36
6	Duration of calls (minutes)	23	362	0.17	0.0015	-0.09	0.18	0.31
7	Number of mails	6	89	0.16	0.1255	0.03	0.04	0.06
8	Time spent with apps of category 'information' (minutes)	23	347	-0.15	0.0041	-0.38	-0.11	0.00
9	Time spent with apps of category 'news' (minutes)	14	230	-0.15	0.0191	-0.27	-0.04	0.14
10	Number of private communication events at work	16	263	0.14	0.0188	-0.13	0.12	0.38
11	Number of communication events	27	418	0.13	0.0087	-0.12	0.21	0.44
12	Duration of phone movement (minutes)	20	314	0.13	0.0167	-0.21	0.05	0.23
13	Number of private communication events	23	356	0.12	0.0191	-0.25	-0.06	0.23
14	Number of instant messages	24	380	0.08	0.1132	-0.15	0.13	0.39
15	Time spent with apps of category 'communication' (minutes)	22	328	-0.08	0.1689	-0.35	-0.01	0.21
16	Time spent with apps of category 'entertainment' (minutes)	21	318	-0.07	0.1955	-0.26	-0.10	0.12
17	Time spent with apps of category 'tools'	23	347	-0.07	0.2199	-0.31	-0.17	0.04
18	Time spent with apps of category 'social networks' (minutes)	14	215	-0.06	0.3741	-0.27	-0.08	0.15
19	Duration of sleep (hours)	27	418	-0.05	0.2974	-0.21	-0.04	0.22
20	Number of occupational communication events at a private place	10	154	0.05	0.5299	-0.10	-0.01	0.20
21	Number of display activations	27	418	0.04	0.4692	-0.10	0.06	0.25
22	Duration of phone usage (minutes)	27	418	0.03	0.4857	-0.10	0.11	0.27
23	Time spent with apps of category 'office' (minutes)	10	157	-0.03	0.7371	-0.34	0.08	0.27
24	Number of occupational communication events	10	154	0.01	0.9420	-0.18	0.05	0.15

appointments, *duration of stay at a private place*, *number of calls* and *time spent with apps of category 'information'*. We remove data of users having no differing values for one or more of the selected features from the dataset, resulting in 205 stress levels stated by 14 users. To evaluate the classification, we remove data produced by one user from the dataset, train the classifier on the remaining data and evaluate the model on the removed data. We repeat this procedure for every user and report the median, minimum and maximum value of accuracy, precision, recall and F-Measure across all runs. We compare the model against a ZeroR classifier (predicting the majority class observed in the training set). The results can be found in Table III. The NaiveBayes classifier performs better than the ZeroR classifier for all metrics. While the differences in accuracy and recall are not too big, the NaiveBayes classifier achieves significantly better precision leading to an increase of median F1-Measure from 0.2 for ZeroR to 0.46 for NaiveBayes. However, predictions by the NaiveBayes classifier are still not accurate enough to detect an individual user's stress level reliably.

V. CONCLUSION

In recent times, ICT usage has been related to a blurring of boundaries between different life domains, which in turn has been associated with several health-hampering effects. In this paper, we focused on the correlation between situational information—user context and ICT usage—and perceived psychological stress. We carried out a study to rank users' acceptance towards different monitoring approaches that can be used for stress detection. Based on the observations in the study, we undertook a non-intrusive approach with the help of a smartphone application, called *StressMon*, relying on smartphone sensing abilities and user self-assessment. We performed a correlation analysis between the situational information collected with our app and the self-assessed stress levels during a field study with 27 users. Based on our results, we observe that longer working hours and higher number of appointments per day have a considerable and significant positive correlation to higher stress levels. Thus, we come to the conclusion that it is possible to detect psychological stress by monitoring situational information. However, for reliable

TABLE III
STRESS LEVEL PREDICTION USING GENERALIZED MODELS

Model	Accuracy			Precision			Recall			F-Measure		
	median	min	max	median	min	max	median	min	max	median	min	max
ZeroR	0.37	0.15	0.78	0.14	0.02	0.61	0.37	0.15	0.78	0,20	0.04	0.69
NaiveBayes	0.46	0.20	0.83	0.47	0.12	0.93	0.46	0.20	0.83	0.46	0.15	0.90

detection of stress, there is no one-fits-all solution. Instead, our approach requires an understanding of individual users or at least user types.

In the future, our plan is to provide users with detailed feedback on personal stressors. Using this feedback, users can change their behavior accordingly. Finally, a long-term goal of this work is to contribute to work-life balance by developing a technological solution that assists users in managing communication situations. For example, the smartphone can manage communication by rejecting, silencing, or delaying incoming communication events. Furthermore, we want to extend the set of collected situational information because it is important that all parameters that may have an impact on stress are included. For example, not only a communication event itself but also the content of the communication may influence the stress level. Concerning the ease of use for the user, open questions are how to reduce the effort for determining the importance, causality, and sentiments of communication, the meaning of places or the mood of the user.

ACKNOWLEDGMENT

This work has been [co-]funded by the Social Link Project within the Loewe Program of Excellence in Research, Hesse, Germany.

REFERENCES

[1] I. Diaz, D. S. Chiaburu, R. D. Zimmerman, and W. R. Boswell, "Communication Technology: Pros and Cons of Constant Connection to Work," *Journal of Vocational Behavior*, vol. 80, no. 2, pp. 500–508, 2012.

[2] R. Dwarakanath, D. Stingl, and R. Steinmetz, "Improving Inter-user Communication: A Technical Survey on Context-aware Communication," *Praxis der Informationsverarbeitung und Kommunikation*, vol. 38, no. 1-2, 2015.

[3] Y. Park and S. M. Jex, "Work-Home Boundary Management using Communication and Information Technology," *International Journal of Stress Management*, vol. 18, no. 2, pp. 133–152, 2011.

[4] N. Chesley, "Blurring Boundaries? Linking Technology Use, Spillover, Individual Distress, and Family Satisfaction," *Journal of Marriage and Family*, vol. 67, no. 5, pp. 1237–1248, 2005.

[5] G. Mark, D. Gudith, and U. Klocke, "The Cost of Interrupted Work: More Speed and Stress," in *ACM CHI*, 2008, pp. 107–110.

[6] G. M. Alarcon, "A Meta-Analysis of Burnout with Job Demands, Resources, and Attitudes," *Journal of Vocational Behavior*, vol. 79, no. 2, pp. 549–562, 2011.

[7] D. Derks, H. van Mierlo, and E. B. Schmitz, "A Diary Study on Work-Related Smartphone Use, Psychological Detachment and Exhaustion: Examining the Role of the Perceived Segmentation Norm," *Journal of Occupational Health Psychology*, vol. 19, no. 1, pp. 74–84, 2014.

[8] S. Cohen, D. Janicki-Deverts, and G. E. Miller, "Psychological Stress and Disease," *Jama*, vol. 298, no. 14, pp. 1685–1687, 2007.

[9] D. C. Ganster and C. C. Rosen, "Work Stress and Employee Health: A Multidisciplinary Review," *Journal of Management*, vol. 39, no. 5, pp. 1085–1122, 2013.

[10] S. Casale, A. Russo, and S. Serrano, "Multistyle Classification of Speech under Stress using Feature Subset Selection based on Genetic Algorithms," *Speech Communication*, vol. 49, no. 10, pp. 801–810, 2007.

[11] K. R. Scherer, "Vocal Communication of Emotion: A Review of Research Paradigms," *Speech Communication*, vol. 40, no. 1, pp. 227–256, 2003.

[12] R. LiKamWa, Y. Liu, N. D. Lane, and L. Zhong, "MoodScope: Building a Mood Sensor from Smartphone Usage Patterns," in *ACM MobiSys*, 2013, pp. 389–402.

[13] R. Wang, F. Chen, Z. Chen, T. Li, G. Harari, S. Tignor, X. Zhou, D. Ben-Zeev, and A. T. Campbell, "StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones," in *ACM Ubicomp*, 2014, pp. 3–14.

[14] P. Adams, M. Rabbi, T. Rahman, M. Matthews, A. Voida, G. Gay, T. Choudhury, and S. Voida, "Towards Personal Stress Informatics: Comparing Minimally Invasive Techniques for Measuring Daily Stress in the Wild," in *EAI PervasiveHealth*, 2014, pp. 72–79.

[15] A. Bogomolov, B. Lepri, M. Ferron, F. Pianesi, and A. S. Pentland, "Pervasive Stress Recognition for Sustainable Living," in *IEEE PerCom Workshops*, 2014, pp. 345–350.

[16] A. Sano and R. W. Picard, "Stress Recognition Using Wearable Sensors and Mobile Phones," in *IEEE ACII*, 2013, pp. 671–676.

[17] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury, "Stresssense: Detecting Stress in Unconstrained Acoustic Environments Using Smartphones," in *ACM Ubicomp*, 2012, pp. 351–360.

[18] D. Metaxas, S. Venkataraman, and C. Vogler, "Image-Based Stress Recognition Using a Model-Based Dynamic Face Tracking System," in *ICCS*, 2004, pp. 813–821.

[19] G. Bauer and P. Lukowicz, "Can Smartphones Detect Stress-Related Changes in the Behaviour of Individuals?" in *IEEE PerCom Workshops*, 2012, pp. 423–426.

[20] D. Pereira and A. Elfering, "Social Stressors at Work and Sleep during Weekends: The Mediating Role of Psychological Detachment," *Journal of Occupational Health Psychology*, vol. 19, no. 1, pp. 85–95, 2014.

[21] Y. Chida and M. Hamer, "Chronic Psychosocial Factors and Acute Physiological Responses to Laboratory-Induced Stress in Healthy Populations: A Quantitative Review of 30 Years of Investigations," *Psychological Bulletin*, vol. 134, no. 6, pp. 829–885, 2008.

[22] F. Togo and M. Takahashi, "Heart Rate Variability in Occupational Health - A Systematic Review," *Industrial Health*, vol. 47, no. 6, pp. 589–602, 2009.

[23] C. Schubert, M. Lambertz, R. A. Nelesen, W. Bardwell, J.-B. Choi, and J. E. Dimsdale, "Effects of Stress on Heart Rate Complexity - A Comparison Between Short-Term and Chronic Stress," *Biological Psychology*, vol. 80, no. 3, pp. 325–332, 2009.

[24] S. D. Kreibig, "Autonomic Nervous System Activity in Emotion: A Review," *Biological Psychology*, vol. 84, no. 3, pp. 394–421, 2010.

[25] A. Gaggioli, G. Pioggia, G. Tartarisco, G. Baldus, M. Ferro, P. Cipresso, S. Serino, A. Popleteev, S. Gabrielli, R. Maimone, and G. Riva, "A System for Automatic Detection of Momentary Stress in Naturalistic Settings," *Studies in Health Technology and Informatics*, vol. 181, pp. 182–186, 2012.

[26] A. Muaremi, B. Arnrich, and G. Tröster, "Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep," *BioNanoScience*, vol. 3, no. 2, pp. 172–183, 2013.

[27] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science*, vol. 35, no. 8, pp. 982–1003, 1989.

[28] "Google APIs for Android - Detected Activity," https://developers.google.com/android/reference/com/google/android/gms/location/DetectedActivity, last accessed: November 9th, 2016.