Wellness Assessment Through Environmental Sensors and Mobile Smartphones

Madison McCarthy and Petros Spachos
School of Engineering, University of Guelph, Guelph, ON, N1G 2W1, Canada
E-mail: mmccar04@mail.uoguelph.ca, petros@uoguelph.ca

***Abstract*—Wellness is an affective state that plays a significant role in our everyday lives, influencing our behaviour, social communication and performance, and even more. Although technological advancements are used to help our society to become more health conscious, wellness and mental health is still lacking in adequate resources, particularly among the student population. In this study, we collected data from 21 participants using mobile sensors and phones. The mobile sensor collected data regarding the temperature, humidity, and luminosity of the environment while the phone provide location information and data processing. The experimental data were analyzed through Perceived Stress Scale (PSS), Pittsburgh Sleep Quality Index (PSQI) and General Well-Being Scale (GWBS). We assess the impact of the location on PSS and PSQI, and the impact of environmental conditions on GWBS. According to experimental result and correlation analysis among the data, luminosity has stronger impact on the wellness than the other two environmental parameters.**

I. Introduction

The desire for the continual advancement of society is in part fueled by rapid technological advancements. These technological advancements not only aim to grow the world but to also help reduce the burden from heavy workloads. Although technology is able to ease some tasks in life, it has also caused the world to become increasingly dynamic with new software and tools being released daily. These technological breakthroughs, which were first developed to ease lives, are now becoming a burden and are reducing the overall health and wellness of individuals.

Many researchers concerned with health and wellness of individuals are still able to utilize these technologies that are hindering society. Prior findings have indicated that there are many factors that can affect the wellbeing of an individual. Some of the factors include traumatic events [1], demand in the workplace [2], social interactions [3] and environmental conditions [4]. Moreover, demographics is known to play a crucial role in one's wellness, with the student demographics being among those that score lower overall.

With this information about wellness in mind, combinations of wearable and mobile sensors with the integration of processing units within smartphone devices have enabled precise data collection geared towards wellness monitoring. More people use wearable sensor for comprehensive health care [5] while smartphone usage can provide useful insights regarding health habits [6]. The combination of external sensors that are highly portable can also enable monitoring of environmental conditions, which can then further help to bring correlations closer to causations for the wellness of society.

In this work, we investigate the correlation between environmental condition and wellness through experimentation. We use mobile sensor along with smartphone to collect data from 21 participants. The experimental results show a correlation between the room luminosity and participants wellness while the location of the experiment do not affect the results.

The rest of this paper is organized as follows: In Section II, the related work is discussed, followed by the system overview in Section III. In Section IV the experiment design and methodology is presented. The experimental results and analysis is in Section V. In Section VI the conclusion is presented.

II. Related Work

In recent years, several frameworks have been proposed to understand a number of factors, such as sleep [7], [8], mood [9], personality type [10] and stress level [11], [12], through wearable/mobile sensors and/or mobile phones.

In [7], the authors used standard mobile phone logs, such as call and text, to reliable predict personality. They used the Pittsburgh Sleep Quality Index (PSQI), and the experimental results showed an increase in the prediction accuracy through the use of mobile data. In [9], the authors used communication history and usage patterns from the phone to infer user's daily mood. They split the user's responses into morning, afternoon and evening sessions. In [11], a wrist sensor was used along with a mobile phone for stress recognition and monitoring with the use of the Perceived Stress Scale (PSS). The authors combine sensor data, accelerometer, and skin conductance with mobile phone logs, call, and text to recognize the level of stress. The experiments lasted five days and showed a correlation between sensor data and phone logs.

The combination of smartphones and biosensor data was utilized in [12] to conduct a four month in study in a real work environment. A multinominal logistic regresison model for the three-stress level classificaiton problem was produced. Environmental monitoring along with biosensor data to identify wellness was proposed in [13]. They used Electrocardiogram (ECG) data for pattern recognition and identification of wellness. In [14], Hemoencephalography (HEG) along with electroencephalography (EEG) and heart rate variability (HRV) were used for safe stress managements and wellness monitoring through the development of a multimodal system.

In [15], wearable sensors were paired with the processing power of smartphones to classify health patterns and academic performance. In [16], only mobile phone data was used to predict the mood of the user. They used phone activity usage along with geographical data to identify an individual frame of mind. The relationship between the environmental conditions through mobile sensors and the productivity was examined in [17].

In this work, we collected stress and sleep data through the PSS and PSQI questionnaires as well as location data from 21 participants. We also collected participant response in the General Well-Being Scale (GWBS) and environmental data during three sessions, in the morning, afternoon and the evening and twice per session, once at the beginning and once after an hour. Then, we investigate whether this data allows us to recognize a correlation between the environmental conditions and the wellness of the participants.

III. System Overview

The proposed framework focuses on daily stress and mood assessment based on environmental sensor data through a mobile sensor and a self-assessment survey with the use of a mobile phone. The system contains a client application based on Android platform and a mobile sensor kit for environmental monitoring. The sensor kit forwards all the collected information to the client application for further processing. The client application also has a number of surveys for the stress and sleep assessment as well as for location and time stamp processing. The collected data from the application are used to examine any correlation information between the environmental data and the stress and mood level.

A. Experimental Setup

For this experiment, the TI SimpleLink Multi-Standard SensorTag Development Kit was used for mobile environmental monitoring and the LG Nexus 5 was used for the client application.

- **SensorTag**. SensorTag [18] is the next-generation IoT development kit, shown in Fig. 1, that combines sensor data with Bluetooth and wireless connectivity. It can support Bluetooth Smart, which was used in this experiment, as well as 6LoWPAN and ZigBee. It also has the CC2650 wireless microcontroller. The battery life operation for the Bluetooth Smart is almost one year. The small size of the kit makes it portable and easy to carry around. It has 8 sensors including, infrared and ambient temperature, ambient light, humidity, barometric pressure, magnet sensors as well as accelerometer, gyroscope and compass. In this experiment, the first three sensors were selected. The size, the battery life and the availability of sensor data make the SensorTag ideal for the introduced experiment.
- **LG Nexus 5**. LG Nexus 5 is an Android smartphone manufactured by LG Electronics. It supports Bluetooth 4.0, which was used in this experiment. The operating system was Android 6.0.1 Marshmallow.

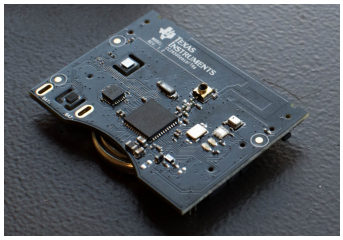


Fig. 1: TI SensorTag Development Kit

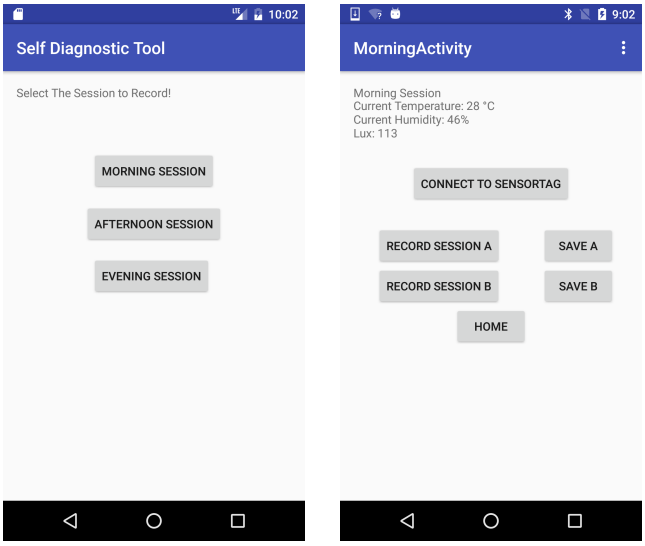
B. Data collection

SensorTag has a number of sensors. In this experiment, the following sensors were used:

- **Infrared and Ambient Temperature Sensor**. The $TMP007$ is an infrared (IR) thermopile sensor that measures the temperature of an object without contacting the object. The integrated thermopile absorbs the IR energy emitted from the object in the sensor field of view. The thermopile voltage is digitized and provided as an input to the integrated math engine, along with the die temperature (TDIE). The math engine then computes the corresponding object temperature.
- **Ambient Light Sensor**. The $OPT3001$ is a single-chip lux meter, measuring the intensity of light as visible by the human eye. The precision spectral response and strong IR rejection of the device enables the $OPT3001$ to accurately meter the intensity of light as seen by the human eye regardless of light source. The strong IR rejection also aids in maintaining high accuracy when mounting the sensor under dark glass. The $OPT3001$ is designed for systems that create light-based experiences for humans.
- **Humidity Sensor**. The $HDC1000$ is a digital humidity sensor with integrated temperature sensor that provides excellent measurement accuracy at very low power. The device measures humidity based on a novel capacitive sensor. The humidity and temperature sensors are factory calibrated. The innovative WLCSP (Wafer Level Chip Scale Package) simplifies board design with the use of an ultra-compact package. The sensing element of the $HDC1000$ is placed on the bottom part of the device, which makes the $HDC1000$ more robust against dirt, dust, and other environmental contaminants. The $HDC1000$ is functional within the full $-40°C$ to $+125°C$ temperature range.

C. Application Implementation

An Android application has been developed for the experiment, providing both connectivity to the SensorTag as well as a means for the participants to enter their responses to the stress, sleep and wellness questionnaires through a User Interface (UI). The UI is comprised of a Main Screen which can be seen in Fig. 2(a), and a Secondary Screen which can be seen in Fig. 2(b).



(a) Main Screen (b) Secondary Screen

Fig. 2: User Interface for the Wellness Monitoring Application

When the participant starts the application, they are taken to the Main Screen which has three selectable options to choose from: the morning session, the afternoon session, and the evening session. These three sessions correspond with the three possible scenarios in which the participant is required to collect information as described in the next section. When one of these three session options is selected, the user is then taken to the corresponding Secondary Screen. From the Secondary Screen the participant must then select 'Connect to SensorTag' which pairs their smartphone device with the SensorTag. Once paired, the participant then selects 'Record Session A' which prompts the participant for responses to the corresponding initial questionnaire for the session. After the questionnaire is completed, 'Save A' must be selected to save the responses as well as log the current environmental sensor readings.

Similar steps are then followed at the end of the session, except the 'B' option must be selected when recording and saving the information. After completing the session on the Secondary Screen, the participant selects 'Home' to navigate back to the Main Screen.

IV. Experiment Design and Methodology

In this section, the experimental approach and setup is described, followed by a brief description of the experiment procedure and the mobile phone surveys.

A. Experimental Setup

Twenty-three healthy participants were recruited for the experiment: 18 males and 5 females with an average age of 24. All participants were aged over 18 years. For the experiment 23 smartphones and SensorTags were used. Part of the experimental equipment is shown in Fig. 3. After the data collection, two participants were excluded from the database as potential outliers since they did not follow the time frame described in the experimental procedure.

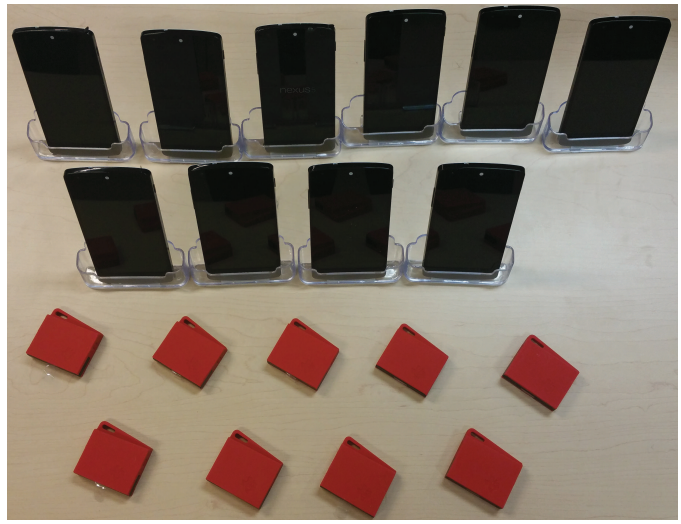


Fig. 3: Equipment used for the Experiment

All participants used the same mobile SensorTag and the same smartphone and OS. For each participant, data was collected for the three sessions: Morning, Afternoon and Evening. For every session, the participant have to record data at the beginning as well as after one hour. The participants were asked to follow their normal everyday routine. As well, the collected data was kept in a separate file and was not available to the participants during the experiment.

For the stress evaluation the Perceived Stress Scale (PSS) [19] was used, with 210 total answers from the participants. PSS is the most widely used psychological instrument for measuring the perception of stress. It is a measure of the degree to which situations in someone's life are appraised as stressful. In this experiment, it was used to evaluate the stress of the participants over the last month. The detail of the questions is illustrated in Table I.

The Pittsburg Sleep Quality Index (PSQI) [20] was also used with 84 total answers from the participants. PSQI is an effective instrument used to measure the quality and patterns of sleep in adults. In this experiment, it was used to evaluate any daytime dysfunction of the participant over the last month. The detail of the questions is illustrated in Table II.

B. Experimental Procedure

The experiment had the following steps:

1) Participants were given the smartphone with the application pre-installed. The participants had to answer the PSS and the PSQI questionnaires before the experiment.
2) A training session was used to explain the participant when they should record data and how to connect the application with the SensorTag and collect the data. Also, the placement of the SensorTag close to the participant was discussed. It is important to make sure the participants do not accidentally block any of the sensors during the experiment.

0 = Never, 1 = Almost Never, 2= Sometimes, 3 = Fairly Often, 4 = Very Often	
Question	Possible Answers
In the last month, how often have you been upset because of something that happened unexpectedly?	0 1 2 3 4
In the last month, how often have you felt that you were unable to control the important things in your life?	0 1 2 3 4
In the last month, how often have you felt nervous and "stressed"?	0 1 2 3 4
In the last month, how often have you felt confident about your ability to handle your personal problems?	0 1 2 3 4
In the last month, how often have you felt that things were going your way?	0 1 2 3 4
In the last month, how often have you found that you could not cope with all the things that you had to do?	0 1 2 3 4
In the last month, how often have you been able to control irritations in your life?	0 1 2 3 4
In the last month, how often have you felt that you were on top of things?	0 1 2 3 4
In the last month, how often have you been angered because of things that were outside of your control?	0 1 2 3 4
In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	0 1 2 3 4

TABLE I: Perceived Stress Scale Questionnaire

0 = Not during the past month, 1 = Less than once a week, 2 = Once or twice a week, 3 = Three or more times a week	
Question	Possible Answers
During the past month, how often have you had trouble sleeping because you cannot get to sleep within 30 minutes ?	0 1 2 3
During the past month, how often have you taken medicine (prescribed or "over the counter") to help you sleep?	0 1 2 3
During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?	0 1 2 3
During the past month, how much of a problem has it been for you to keep up enthusiasm to get things done?	0 1 2 3

TABLE II: Pittsburg Sleep Quality Index Questionnaire

3) Participants were given the smartphones and the SensorTag for a day.
4) Participants returned the equipment to the laboratory and completed a post-experiment survey about their mood and stress in the last day.

C. Mobile Phone Survey

On the Android phones, location and mood were also monitored in addition to the PSS and PSQI surveys.

For the location, the participants were asked to do the experiment only indoors and select from four different options:

1) Home (less than two people)
2) Home (more than two people)
3) Laboratory (less than five people in the room)
4) Laboratory (more than five people in the room)

The participants can change location between sessions, however, they need to finish a session at the same location they started.

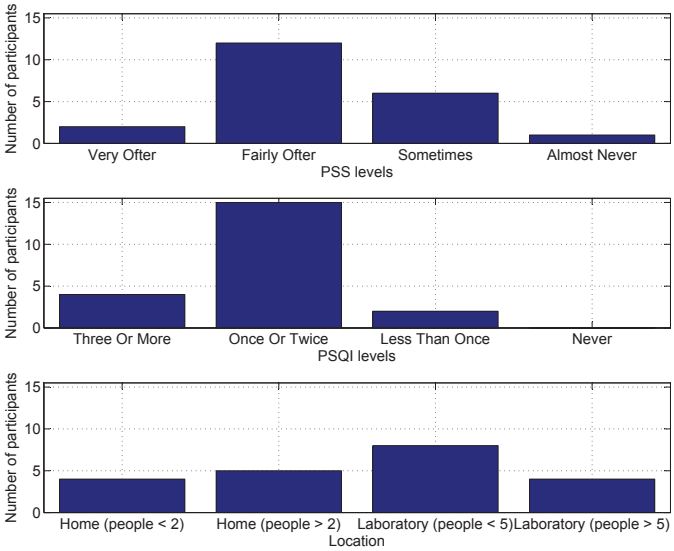


Fig. 4: Distribution of PSS, PSQI and Location from 21 Participants

For the mood, the 18 questions from the the General Well-Being Scale (GWBS) [21] were used.

D. Experimental Sessions

The participants had to do the experiments in three sessions during the day:

- In the **morning session** (6am- noon),
- the **afternoon session** (noon- 6pm) and
- the **evening session** (6pm - midnight).

For every session, the participants had to connect the application with the SensorTag to record the environment data twice: once at the beginning of the session and once after one hour. Hence, each participant had to answer the GWBS questionnaire six times in total. This would help in the data analysis to correlate any change in the mood with the environmental conditions in the room at the beginning of the session and after one hour.

V. Results and Analysis

In this section we describe the results of our experiments.

A. Classification of Long-Term Profile

For the long-term profile, the participants were categorized based on their responses in the PSS, PSQI and Location questionnaire, since these do not change between the beginning and the end of the session. From the PSS and PSQI, we define four groups of participants. The distribution of the scores is illustrated in Fig. 4.

PSS is a score from 0 to 40 with four categories: Very Often (31-40), Fairly Often (21-30), Sometimes (11-20) and Almost Never (0-11). The higher the score the higher the perceived stress. According to the results, the majority of the participants (score above 21) had high stress levels, which can be explained since all of them are undergraduate students during the term.

PSQI is a score between 0 to 12 with four categories: Three or more (9 - 12), Once or twice (6 - 8), Less than once (3-5) and Never (0-2). A PSQI score above 5 was considered as poor sleep quality. According to the results, PSQI seems to follow the PSS levels. The linear correlation between the PSS and PSQI levels is 0.6265, hence, this is an indicator that there is a correlation between the stress level and the sleep pattern.

We also calculate the correlation between the location and the PSS and the location and the PSQI. Table III shows the results.

	PSS	PSQI	Location
PSS		0.6265	0.2816
PSQI	0.6265		0.3620

TABLE III: Correlation Between PSS, PSQI and Location

According to the correlation values, the participant's location during the experiment does not affect the PSS and/or the PSQI levels.

B. Correlation Analysis of Short-Term Profile

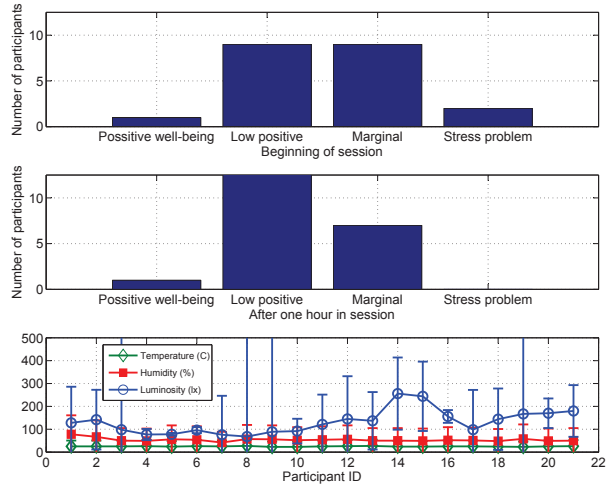
From the $2,268$ answers on the GWBS, we define four groups of participants, with the corresponding score in parenthesis: Positive well-being (81-110), Low positive (76-80), Marginal (71-75) and Stress problem (56-70). Then, we summarize the results for the three session in a day and the environmental parameters at the beginning of a session and one hour after.

To examine any correlation between the three environmental values and the GWB scale, Pearson correlation was used and the results for the different sessions are shown in Table IV.

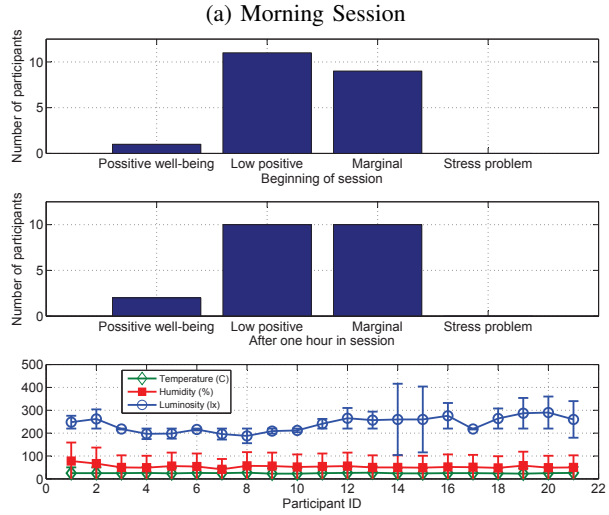
Morning Session (6am - noon)			
	Temperature	Humidity	Luminosity
GWB	-0.1634	-0.0360	0.7636
Afternoon Session (noon - 6pm)			
	Temperature	Humidity	Luminosity
GWB	-0.1854	-0.4051	0.2398
Evening Session (6pm - midnight)			
	Temperature	Humidity	Luminosity
GWB	0.2354	0.3693	-0.8355

TABLE IV: p-value of Pearson Correlation Coefficient for GWBS for the Three Sessions

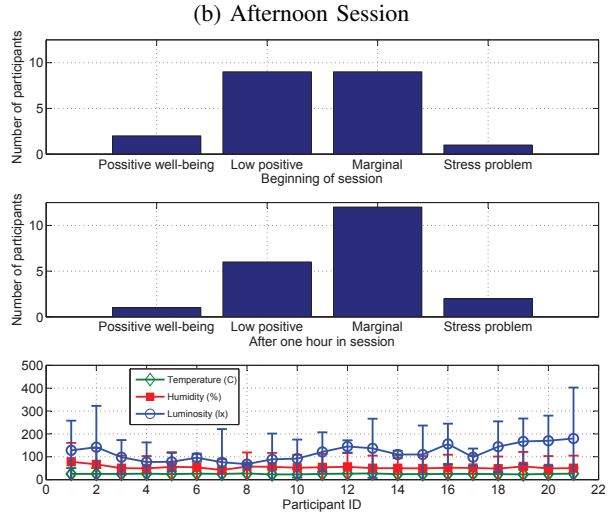
Fig. 5(a) shows the results for the morning session. At the beginning of the session most of the participants are at the Marginal level and above (17 out of 21), with the number of the participants in the Low positive and Marginal level equal. After an hour, some of the participants from the Marginal and Stress problem level moved to the Low positive level. At the same time, we monitored the environmental conditions. The temperature and the humidity remains similar which can be seen from the error bars in the third figure of Fig. 5(a), which is expected since both the home and the laboratory are indoor environment with minimum variation in these two parameters.



(a) Morning Session



(b) Afternoon Session



(c) Evening Session

Fig. 5: Distribution of GWBS for the Three Sessions from 21 Participants

On the other hand, the luminosity variation is high. This can be used as an indicator for correlation between luminosity of the room and the mood of the person, as it is also shown on Table IV through the p-values for luminosity.

For the afternoon session, shown in Fig. 5(b) the participants have similar scores in the GWB scale at the beginning and one hour after. At the same time, the environmental values show negligible variation. According to the Pearson correlation values in Table IV, there is no linear correlation between the environmental data and the GWBS scores.

For the evening session, the results are shown in Fig. 5(c). In this session, the participants tend to move toward lower scores at the GWBS scale. At the beginning of the session, ten participants had a GWBS score above 80 while an hour after, only six of them remain with a similar score. At the same time, the variation in temperature and humidity is negligible while the luminosity is high. There is a correlation between luminosity and the mood variation, according to Pearson correlation in Table IV.

According to experimental results, variation in the luminosity of a room can affect the mood of the people in the room. Another important insight from the experiment is related to the change of the luminosity. When the luminosity increases during the session, as in the morning session, the participants mood changes towards higher GWBS scores. On the other hand, when the luminance decreases, the participants mood changes towards lower GWB scores. However, the results of this experiments can be used only as indicators. Further, experimentation with more participants should be conducted to evaluate the indicators of this work.

VI. Conclusion

In this paper, we investigate the correlation between environmental data and wellness through experimentation. According to the results, great changes in luminosity can affect a person wellness. We also find that the experiment location do not affect the stress or the sleep pattern of the participants. However, more experimentation is necessary with larger population to validate the insights of this work and also examine more parameters that can affect wellness.

VII. Acknowledgment

This research was supported by a grant from Google and a matching grant from NSERC/CRD.

References

[1] S. Collins and A. Long, "Working with the psychological effects of trauma: consequences for mental health-care workers a literature review," *Journal of Psychiatric and Mental Health Nursing*, vol. 10, no. 4, pp. 417–424, 2003.

[2] St. Einarsen and M. B Nielsen, "Workplace bullying as an antecedent of mental health problems: a five-year prospective and representative study," *International Archives of Occupational and Environmental Health*, vol. 88, no. 2, pp. 131–142, 2015.

[3] J. Mirowsky, *Analyzing Associations Between Mental Health and Social Circumstances*, pp. 143–165, Springer Netherlands, Dordrecht, 2013.

[4] H. L. Berry, K. Bowen, and T. Kjellstrom, "Climate change and mental health: a causal pathways framework," *International Journal of Public Health*, vol. 55, no. 2, pp. 123–132, 2010.

[5] D. Metcalf, S. T. J. Milliard, M. Gomez, and M. Schwartz, "Wearables and the internet of things for health: Wearable, interconnected devices promise more efficient and comprehensive health care," *IEEE Pulse*, vol. 7, no. 5, pp. 35–39, Sept 2016.

[6] A. Rahmati and L. Zhong, "Studying smartphone usage: Lessons from a four-month field study," *IEEE Transactions on Mobile Computing*, vol. 12, no. 7, pp. 1417–1427, July 2013.

[7] S. T. Moturu, I. Khayal, N. Aharony, W. Pan, and A. Pentland, "Using social sensing to understand the links between sleep, mood, and sociability," in *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on*, Oct. 2011, pp. 208–214.

[8] Z. Chen, M. Lin, F. Chen, N. D. Lane, G. Cardone, R. Wang, T. Li, Y. Chen, T. Choudhury, and A. T. Campbell, "Unobtrusive sleep monitoring using smartphones," in *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare*, ICST, Brussels, Belgium, Belgium, 2013, PervasiveHealth '13, pp. 145–152, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[9] R. LiKamWa, Y. Liu, N. D. Lane, and L. Zhong, "Moodscope: Building a mood sensor from smartphone usage patterns," in *Proceeding of the 11th Annual International Conference on Mobile Systems, Applications, and Services*, New York, NY, USA, 2013, MobiSys '13, pp. 389–402, ACM.

[10] J. de Montjoye, Y. A.and Quoidbach, F. Robic, and A. Pentland, "Predicting personality using novel mobile phone-based metrics," in *Proceedings of the 6th International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction*, Berlin, Heidelberg, 2013, SBP'13, pp. 48–55, Springer-Verlag.

[11] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in *Proceedings of the 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, Washington, DC, USA, 2013, ACII '13, pp. 671–676, IEEE Computer Society.

[12] 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.

[13] Y. Jung and Y. I. Yoon, "Wellness contents recommendation based on human emotional and health status using em," in *2015 Seventh International Conference on Ubiquitous and Future Networks*, July 2015, pp. 977–981.

[14] U. Ha, Y. Lee, H. Kim, T. Roh, J. Bae, C. Kim, and H. J. Yoo, "A wearable eeg-heg-hrv multimodal system with simultaneous monitoring of tes for mental health management," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 9, no. 6, pp. 758–766, Dec 2015.

[15] A. Sano, A. J. Phillips, A. Z. Yu, A. W. McHill, S. Taylor, N. Jaques, C. A. Czeisler, E. B. Klerman, and R. W. Picard, "Recognizing academic performance, sleep quality, stress level, and mental health using personality traits, wearable sensors and mobile phones," in *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, June 2015, pp. 1–6.

[16] Y. Ma, B. Xu, Y. Bai, G. Sun, and R. Zhu, "Daily mood assessment based on mobile phone sensing," in *2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks*, May 2012, pp. 142–147.

[17] S. van der Valk, T. Myers, I. Atkinson, and K. Mohring, "Sensor networks in workplaces: Correlating comfort and productivity," in *Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2015 IEEE Tenth International Conference on*, April 2015, pp. 1–6.

[18] Texas Instruments, "SimpleLink SensorTag," http://www.ti.com/ww/en/wireless_connectivity/sensortag2015/?INTC=SensorTag&HQS=sensortag.

[19] S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," *Journal of Health and Social Behavior*, vol. 24, no. 4, pp. 385–396, 1983.

[20] D.J. Buysse, C.F. Reynolds, T.H. Monk, S.R. Berman, and D.J. Kupfer, "A global measure of perceived stress," *Psychiatry Research*, vol. 28, no. 2, pp. 193–213, 1989.

[21] A. F. Fazio, "A concurrent validation study of the nchs general well-being schedule," *National Center for Health Statistics, Hyattsville, MD*, vol. 24, no. 4, pp. 385–396, 1977.