HealthyClassroom

A Proof-of-Concept Study for Discovering Students' Daily Moods and Classroom Emotions to Enhance a Learning-teaching Process using Heterogeneous Sensors

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Abstract: This paper introduces an interactive system that discovers students' daily moods and classroom emotions to enhance the teaching and learning process using heterogeneous sensors. The system is designed to enable (1) detecting students daily moods and classroom emotions using physiological, physical activities, and event tags data coming from wristband sensors and smart-phones, (2) discovering association/correlation between students' lifestyle and daily moods, and (3) displaying statistical reports and the distribution of daily moods and classroom emotions of students, both in individual and group modes. A pilot proof-of-concept study was carried out using Empatica E4 wristband sensors and Android smart-phones, and preliminary evaluation and findings showing promising results are reported and discussed.

1 INTRODUCTION

The influence of moods/emotions on education has been researched for decades. Many researches try to understand the impact of moods/emotions on different aspects of education in order to create a better learning environment for students (Pekrun, 1992)(Bryan et al., 1996)(Titsworth, 2010).

Generally, there are four approaches to understand the impact of moods/emotions in learning and working environments: (1) *paper-based questionnaires* (Pekrun, 1992)(Bryan et al., 1996)(Lewine et al., 2015)(Liew and Tan, 2016), (2) *digital-based event tags* (Rachuri et al., 2010)(Sottilare and Proctor, 2012)(Kikamwa et al., 2013)(Gjoreski et al., 2015), (3) *physiological signals* (Wioleta, 2013)(Hang et al., 2014)(Valenza et al., 2014), and (4) *hybrid* (Sano and Picard, 2013)(Zenonos et al., 2016).

The first approach mostly uses survey methods to get samples. This leads to a small volume of samples, limitations in tracking mood/emotion states, static and inflexible way to collect data, as well as bias and delay in providing answers. These factors influence expected outcomes and make it hard to generalize the research into higher conceptual levels, scale up into larger scopes, as well as enabling real-time monitoring and prediction/detection of moods and emotions of learners.

The second approach uses computers or smart-phones as a portal to collect data from users for detecting and/or predicting mood and emotion states. It is common in the methods of this approach to design an application (or a website) accessed by smart-phones or computers with predefined mood/emotion categories and levels. Users interact with this application to input related information for detection of moods and emotions. Where relevant, prediction models could be built using collected data to allow automatic prediction of users moods/emotions. Nevertheless, this approach cannot prevent bias of answers since users sometimes find it difficult or inconvenient to determine exactly how they feel at any given time.

The third approach leverages on physiological signals collected from users using wearable sensors. Physiological data could be a good alternative to conveniently capture information from humans, and to objectively detect moods/emotions. This is because such data directly reflects, at least as far as the chosen signal sources are concerned, how human bodies react in a surrounding environment with respect

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to any faced issues (Wioleta, 2013). The wearable sensors used to collect such physiological data vary from uncomfortable bio-sensors (Hang et al., 2014), comfortable t-shirts with integrated fabric electrodes and sensors (Valenza et al., 2014), to wristband sensors (Thapliyal et al., 2017)(Koskimaki et al, 2017). Among these types of sensors, wristband sensors are known to be more comfortable in terms of mobility, mounting location, and continuous skin connection.

The last approach combines smart-phones and wearable sensors to collect physiological data, human behaviour, and moods/emotions tags from users as well as displaying the detected results to users via smart-phones (Sano and Picard, 2013)(Zenonos et al., 2016). This approach leverages all advantages of smart-phones and wearable sensors to collect data and detect moods/emotions while still maintaining high level of convenience and freedom for users.

From psychological perspective, moods and emotions are used to express feelings that people experience. Although these words are frequently used interchangeably, there are many differences between moods and emotions (Beedie et al., 2005). The main ones are related to intensity, the objects people react to, and the duration they last. While emotions are intense feelings directed at someone or something, moods are feelings that tend to be less intense and often (though not always) lack a contextual stimulus (Robbins et al., 2010). Besides, a mood may last longer than an emotion (e.g. hours/days versus seconds/minutes) (Beedie et al., 2005).

In order to avoid any misunderstanding, in this paper we use *emotions* for expressing the feelings of students in a classroom where students (university level in current study) react to a lecturer, a lesson activity, or their classmates within a limited time; and *moods* for out-of-classroom feelings that are heavily influenced by the environment, physiology, or mental state. In other words, the contexts of *emotions* and *moods* are within-a-classroom and throughout-the-day, respectively.

Many researches have tried to understand the impact of moods and emotions on education based on two independent contexts: *in classroom* (Hang et al., 2014)(Lewine et al., 2015)(Liew and Tan, 2016)(Mainhard et al., 2017), and *on campus* (Bryan et al., 1996)(Febrilia and Warokka, 2011)(Kikamwa et al., 2013)(Gjoreski et al., 2015). Although these studies have found useful results, there are still open questions that need to be investigated thoroughly:

1. The research carried out by (Mainhard et al., 2017) highlights that the students' emotional experiences can be driven by evolving the specific relationship between lecturers and students during class time. Therefore, it would be very useful to have a tool that can visualize students' emotions during a class to allow a lecturer to flexibly change his/her educational method or activity in order to stimulate positive emotions that enhance the teaching-learning process.
2. There seem to be no work we are aware if on discovering association/correlation between *daily moods* and *classroom emotions* of learners. For example, if one student comes to a class with negative moods (e.g. nervous, stressed) due to not yet finishing his/her assignment though staying late last night, whether this student can have *excited and relaxed* emotions during the class time though a classroom's atmosphere is very exciting?
3. There are few studies that investigated association/correlation between a student's lifestyle and his/her daily moods. In this study, we are interested to investigate, for example, if long-term negative moods of a student are correlated with a certain lifestyle (e.g. staying up late, exercising too much, lack of physical activity, etc.). This may enable student's counseling to be triggered automatically and provides valuable input for the counseling process.

This paper addresses the above questions at a university level by creating a framework, namely *HealthyClassroom*, which uses wristband sensors and smart-phones to collect physiological, physical activities, and event tags data to detect and visualize students' daily moods and classroom emotions, as well as to discover any association/correlation between students' lifestyles and daily moods.

2 HEALTHYCLASSROOM

Figure 1 illustrates an overview of the *HealthyClassroom* framework. In this context, *mood* and *emotion* can be used interchangeably according to the context (i.e. if the framework is applied inside a classroom, *emotion* is considered, otherwise *mood* is used). The physiological, location, and event tags data (when users provide input by tagging specific events) are sent from wristband sensors and smart-phones to a cloud-computing platform. Using this data, students moods and emotions are then detected/recognized and displayed on a website that can be accessed by lecturers and/or administration users. The timeliness of such information provides valuable input to understand the ongoing teaching-learning process and improve the delivery and interaction between lecturers and

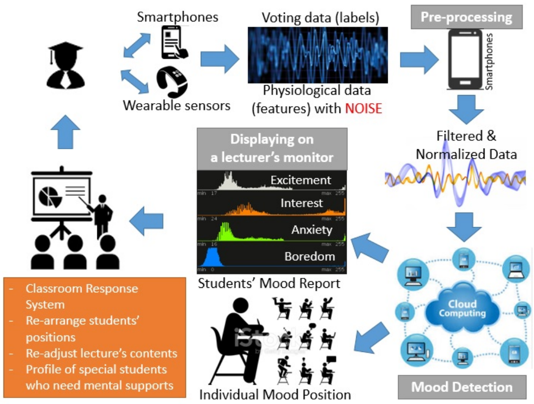

Figure 1: The HealthyClassroom Overview.

students. The data generated from activities outside the classroom can be used not only to directly influence the learning process, but also to understand the social daily activities of students and their mental health, in addition to triggering necessary counseling intervention.

The system works as follows: The wristband devices worn by students frequently send physiological and location signals to smart-phones via Bluetooth protocol. The smart-phones do preprocessing (i.e. data filtering and normalizing) and capture tagging data from students (if provided). For example, students may choose at different times to give feedback about the current mood/emotion they feel, or the physical activity they are doing. This is performed using a smart-phone application synchronized with the wristband sensor, and essentially helps in generating labeled data crucial at the starting phase of our study. The data is then sent to a cloud-computing system for storage and analysis. In the cloud, training and re-training tasks to create classifiers for each type of mood/emotion are triggered according to predefined models and thresholds. These classifiers will detect mood/emotion along a time-axis. The results can be displayed - in different forms - on a website that can be accessed by concerned users for further actions such as re-arranging students classroom positions, re-adjusting lessons content, activating classroom response system, counseling identification for students who exhibit negative moods and emotions for a long time, etc.

2.1 Models of Moods/Emotions

In our work, we refer to (Wioleta, 2013) for a survey on emotion's models based on various theories of emotions and affect models developed for different application fields. The conclusion is that creating a

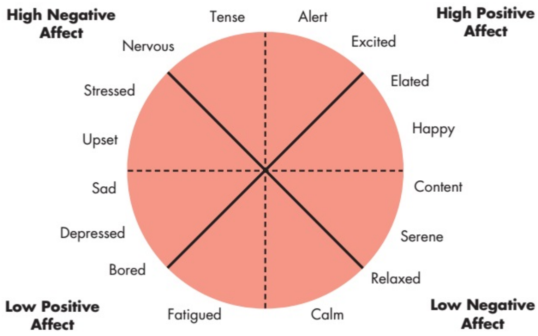

Figure 2: The structure of mood, reused from (Robbins et al., 2010).

model of emotion is not a trivial problem. In this research, we use the affect structure presented in (Robbins et al., 2010), and illustrated in Figure 2.

2.2 Affect Detection and Lifestyle-Mood Pattern Discovery

Figure 3 illustrates how the association/correlation among lifestyle, daily moods, classroom emotions, and classroom interaction can be taken into account and visualized properly. There are four processes run synchronously: (1) physical activities (PA) detection using accelerometer and gyroscope data extracted from smart-phones, (2) daily moods (DM) recognition using physiological data collected from wristband sensors, (3) classroom emotions (CE) discovery using physiological data collected from wristband sensors, and (4) association/correlation uncovering using the outputs of the three previous processes.

The first process is built by utilizing the PHASOR system (Dao et al., 2017) where accelerometer and gyroscope collected from smart-phones are translated into a set of human daily activities, namely *standing, walking, jogging, up-stairs, downstairs,* and *sitting*. We have also added one more activity, *driving*, to this set.

The second and third processes are constructed based on the concepts shown in Figure 1. Figure 4 illustrates the mechanism used to detect moods and emotions using physiological signals and event tags.

The fourth process leverages the research presented in (Laleh et al., 2015) to discover lifestyle-mood patterns (i.e. association/correlation between lifestyle and daily moods of students). In this case, we assume that human daily activities could have association/correlation with moods. In other words, a sequence of activities could lead to a certain mood status during a period of time. We formalize this association as follows. Let E_i denote an activity at time t, Δt_i

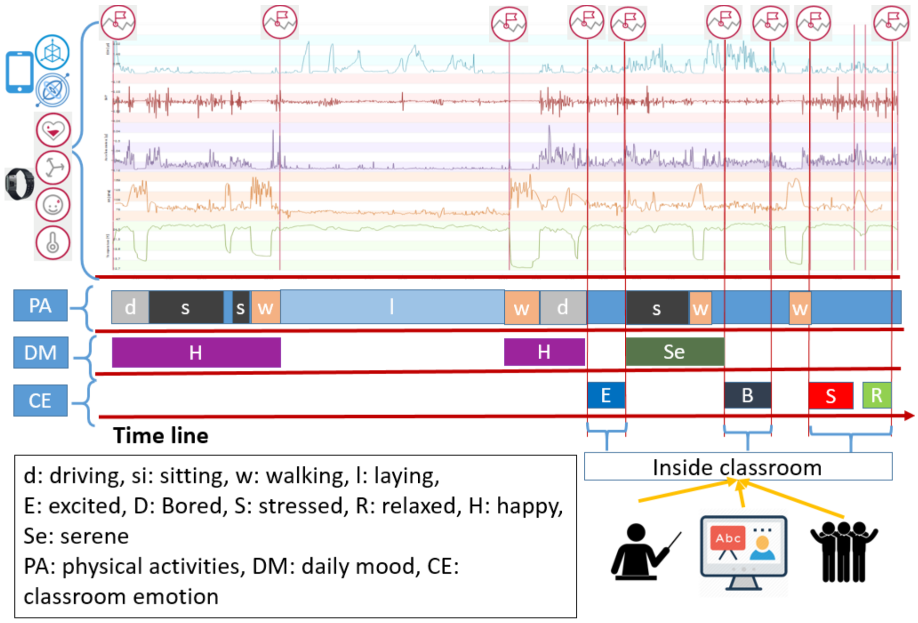

Figure 3: The personal dashboard of associations/correlations among lifestyle, daily moods, and classroom emotions of a student visualized in HealthyClassroom.

denote the "time lag" between two consecutive activities E_i and E_{i+1}, and F_j represent a mood's label. The association/correlation between n consecutive activities and mood status F can be expressed by the pattern

$$\rho = (F_p : E_1; \Delta t_1 E_2; \Delta t_2 E_3; \ldots; \Delta t_{n-1} E_n : F_c) \qquad (1)$$

where F_p and F_c is the previous and current mood statuses. Then, the pattern recognition component employs an extended finite-state automata (FSA). The automaton is designed to contain a finite number of states and state transitions. The FSA is a 5-tuple, (OS, TS, E, F_p, F_c), consisting of a finite set of ordinary states (OS), time states (TS), directed edges (E), a start state $F_p \in OS$ and a final or acceptance state $F_c \in OS$. The "Algorithm 1" described in (Laleh et al., 2015) is utilized to count the frequencies of patterns.

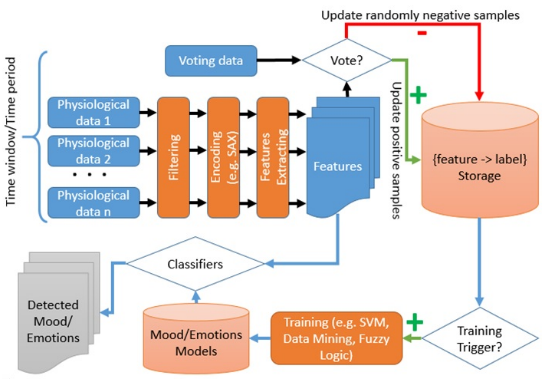

Figure 4: The Mood/Emotion Detection Mechanism.

If a pattern occurs frequently, it might be significant and could be, in our context, argued as a lifestyle-mood pattern.

3 EXPERIMENTAL RESULTS

In this section, we describe HealthyClassroom's working environment and performance evaluation. Currently, the HealthyClassroom works as a proof-of-concept framework for discovering students' daily moods and classroom emotions to enhance a teaching-learning process. Therefore, only the three questions mentioned in Section 1, as a significant contribution of the HealthyClassroom, are considered for evaluation.

3.1 Working Environment Setting

We use the Empatica E4 wristband (E4) [1] as a wearable sensor for our system.

The E4 is recently used to collect physiological data for early detection of migraine attacks (Koskimaki et al, 2017), and it is shown that this data is good enough for doing experiments. The E4 has the following sensors: (1) *Photoplethysmograph (PPG) sensor*: measures blood volume pulse (BVP) from

[1] https://www.empatica.com/e4-wristband

which heart rate, heart rate variability (HRV), and other cardiovascular features may be derived; (2) *3-axis Accelerometer* (ACC): captures motion-based activity; (3) *Electrodermal Activity (EDA) sensor*: measures sympathetic nervous system arousal and to derive features related to stress, engagement, and excitement; and (4) *Infrared Thermopile* (TEMP): reads peripheral skin temperature. Besides, E4 also has a function called *Event Mark Button* that is used to tag events and associate them with physiological signals. There are three working modes by which users can collect their data: (1) *Recording Mode*: uses an internal memory to store data that can be copied via USB port later; (2) *Streaming Mode*: connects to a smartphone or desktop computer via Bluetooth using *Real-time App* and *mobile API* for desktop and mobile devices, respectively; and (3) *Upload to Connect*: uses Empatica's secure cloud platform. Figure 5 displays one example of data collected from E4.

We have developed a smart-phone app that gets activated by the E4 *Event Mark Button*, which is used to tag the events using the list of mood/emotion labels mentioned in subsection 2.1. This app can run with manual and semi-automatic options. The former gets a label from the user, and the latter generates a label by using the second and third processes described in subsection 2.2. A user can re-tag an auto-generated label if he/she does not agree with the label generated by the system.

We have also built a website through which users can login to visualize their information including physical activities (PA), daily moods (DM), and classroom emotions (CM). If the user has a lecturer role, he/she can visualize his/her students information in real-time mode, to enable taking quick actions such as adjusting lesson activities (maybe to achieve more positive in-class emotions).

We have also implemented four system components corresponding to the four processes mentioned in subsection 2.2: (1) Physical Activities Detection, (2) Mood Detection, (3) Emotion Detection, and (4) Lifestyle-mood Pattern Discovery.

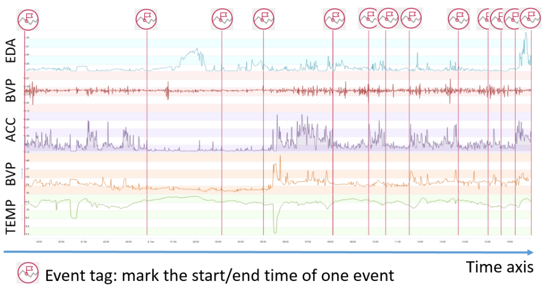

Figure 5: Physiological data collected by E4, recorded from 18:20 November 7, 2017 to 17:00 November 8, 2017.

3.2 Evaluation

We have asked students and lecturer of one university course to join our pilot experiment (15 students, 1 lecturer, *Introduction to Programming* course). Each student is requested to wear the E4 wristband for continuous three weeks time, except during the time the take bath.

The first week: we collect samples for training mood/emotion detection models. Students reported some inconvenience in continuously tagging events (e.g. choosing mood/emotion labels), especially during class time since emotions change very fast. We also use the data of this week to track the ratio of overall positive and negative emotions.

The second week: we automatically detect in-class emotions, and ask the lecturer to monitor the students emotions visualized by the system, and to adjust teaching activity or classroom setting to improve classroom emotional climate. The system showed that high positive emotions have increased by 20% compared to previous week. Currently, we do not have strong evidence to attribute this improvement to the adjustment alone, but we argue that knowing students' emotions is an important factor that helps to improve classroom emotional climate. In this week as well, we start to discover the lifestyle-mood patterns.

The third week: at the beginning of this week, we released the lifestyle-mood patterns with the highest negative emotions for each student, and asked them to try to change these patterns. For example, one pattern was that staying up late was associated with "stressed" emotion. Another pattern was that *sitting* for long time in campus was associated with "bored" emotion. At the end of this week, we noticed an increase of 30% for high positive emotions compared to the first week. Again, we do not have strong support for the reason of this improvement, but we argue that discovering the lifestyle-mood pattern could be another factor that improves classroom emotional climate.

It is important to note that from the second week onwards, the system can automatically detect moods/emotions and daily activities, and therefore the events tagging has decreased (i.e. only for correcting wrong labels). Therefore, students expressed feeling more comfortable with the HealthyClassroom compared to the first week.

By surveying students feedback, ten out of fifteen students (66.7%) agreed that HealthyClassroom can help them control their lifestyle-mood relation as well as improve their passion in studying. Two students (13.3%) felt nothing changed with the use of HealthyClassroom. Three students (20%) had neutral comments.

The lecturer felt excited when using HealthyClassroom. Nevertheless, continuously monitoring the percentage of positive emotions and finding a way to cheer up the class somehow distract the teaching process. There should be a function that can alert the lecturer when the emotion climate reaches a certain level so that the lecturer can adjust himself/herself better. This solution can alleviate the burden of monitoring the fluctuation of classroom emotions continuously. This matter is recognized and will be adopted in future works.

Since the human daily activity, mood, and emotion detectors are built by using PHASOR (Dao et al., 2017), we have used the same evaluation scheme to evaluate the first three processes. According to our evaluation, the first process (i.e. activities detection) reaches 90% accuracy while the second (i.e. moods detection) and the third (i.e. emotions detection) gain 65.2% and 57.3%, respectively.

4 CONCLUSIONS

In this paper, we introduced the HealthyClassroom framework that works with wristband sensors, smartphones, and cloud computing environment to analyze the impact of students' daily moods, classroom emotions, and lifestyle on the teaching-learning process. The HealthyClassroom provides a data visualization for lecturers to track classroom emotions in real-time, to enable adjusting lessons' activities in order to improve students positive emotions. Last but not least, by getting insights from recorded personal-lifelog data, including lifestyle-moods patterns, students can be counseled on how to improve their studying process by changing their lifestyle activities.

Although the HealthyClassroom currently is a pilot proof-of-concept study, important findings have have been gained. Some interesting lifestyle-moods patterns are discovered that can help lecturers and students adjust their teaching-learning behaviors.

We recognize that our current experimental setup is limited to a small uncontrolled study, and in the future it is important to address this issue in order to reliably conclude if the use of HealthyClassroom reflects positively on the teaching-learning process. Besides, it will be interesting to further analyze the correlation between the emotions of different students, and to see if a students mood/emotion could be influenced by another student(s). To tackle such investigations, it might be important to monitor classroom environment using some sort of crowd-sensing (e.g. activating smart-phones' microphones to measure noise levels, monitoring smart-phone-user interaction to identify students' distraction, indoor location to detect possible students interactions, etc.).

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REFERENCES

Beedie, C.J. and Terry, P.C. and Lane, A.M. (2005). Distinctions between emotion and mood. *COGNITION AND EMOTION*. 19 (6), 847-878

Bryan, T. and Mathur, S. and Sullivan, K. (1996). The Impact of Positive Mood on Learning. *Learning Disability Quarterly*. 19 (3), 153-162

Dao, M.S. and Dang-Nguyen, D.T. and Riegler, M. and Gurrin, C. (2017) Smart lifelogging: recognizing human activities using PHASOR. In Proc. of *6th Int. Conf. on Pattern Recognition Applications and Methods (ICPRAM 2017)*. 24-26.

Febrilia, I. and Warokka, A. (2011). The Effects of Positive and Negative Mood on University Students Learning and Academic Performance: Evidence from Indonesia. In Proc. of *3rd Int. Conf. on Humanities and Social Sciences*. 1-12

Gjoreski, M. and Gjoreski and H. and Lustrek, M. and Gams, M. (2015). Automatic detection of perceived stress in campus students using smartphones. *Intelligence Environment*. 132-135

Hang, A. and Goronzy, S. and Schaich, P. and Williams, J. (2014). Emotion Recognition Using Bio-Sensors: First Steps Towards an Automatic System. *Tutorial and Research Workshop on Affective Dialogue Systems*. 36-48

Kikamwa, R. and Liu, Y.X. and Lane, N.D. and Zhong, L. (2013). MoodScope: Building a Mood Sensor from Smartphone Usage Patterns. In Proc. of *MobiSys13*.1-13

Koskimaki, H. et al (2017). Early detection of migraine attacks based on wearable sensors: experiences of data collection using Empatica E4. In Proc. of *the 2017 ACM Int. Joint Conf. on Pervasive and Ubiquitous Computing and the 2017 ACM Int. Symposium on Wearable Computers (UbiComp '17)*. 506-511

Laleh, J. and Dao, M.S. and Jain, R. and Zettsu, K. (2015) Complex asthma risk factor recognition from heterogeneous data streams. In Proc. of *IEEE Int. Conf. on Multimedia and Expo Workshops (ICMEW)*

Lewine, R. and Sommers, A. and Waford, R. and Robertson, C. (2015). Setting the Mood for Critical Thinking in the Classroom. *Int. Journal for the Scholarship of Teaching and Learning*. 9 (2), Article 5, 1-4

Liew, T.W. and Tan, S.M. (2016). The Effects of Positive and Negative Mood on Cognition and Motivation in Multimedia Learning Environment. *Educational Technology and Society*. 19 (2), 104115

Mainhard, T. and Oudmana, S. an Hornstra, L. and Bosker, R.J. and Goetz, T. (2017) Student emotions in class: The relative importance of teachers and their interpersonal relations with students. *Learning and Instruction*. ISSN 0959-4752

Pekrun, R. (1992). The Impact of Emotions on Learning and Achievement: Towards a Theory of Cognitive/Motivational Mediators. *Applied Psychology: An International Review*. 41 (4), 359-376

Rachuri, K.K. et al. (2010). EmotionSense: A Mobile Phones based Adaptive Platform for Experimental Social Psychology Research. In Proc. of *UbiComp10*. 281-290

Robbins, S.P. and Judge, T.A. and Campbell, T. (2010) Organizational Behaviour. *Pearson*. ISBN-10: 0273719394, ISBN-13: 9780273719397

Sano, A. and Picard, R.W. (2013). Stress Recognition using Wearable Sensors and Mobile Phones. In Proc. of *Humaine Association Conference on Affective Computing and Intelligent Interaction*. 671-676

Sottilare, R.A. and Proctor, M. (2012). Passively Classifying Student Mood and Performance within Intelligent Tutors. *Educational Technology and Society*. 15 (2)

Thapliyal, H and Khalus, V. and Labrado, C. (2017). Stress Detection and Management: A Survey of Wearable Smart Health Devices. *IEEE Consumer Electronics Magazine*. 6 (4). 64-69

Titsworth, S. and Quinlan, M.M. and Mazer, J.P. (2010) Emotion in Teaching and Learning: Development and Validation of the Classroom Emotions Scale. *Communication Education*. 59 (4), 431-452

Valenza, G. et al. (2014). Wearable Monitoring for Mood Recognition in Bipolar Disorder based on History-Dependent Long-Term Heart Rate Variability Analysis. *IEEE Journal of Biomedical and Health Informatics*. 18 (5), 1625-1635

Wioleta, S. (2013). Using Physiological Signals for Emotion Recognition. In Proc. of *6th Int. Conf. on Human System Interactions (HSI)*. 556-561

Zenonos, A. et al. (2016). HealthyOffice: Mood Recogntion At Work Using Smartphones and Wearable Sensors. In Proc. of *PERCOM Workshop*. 1-6