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# Towards Social Enterprise with Internet of Office Desks

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## Abstract.

Social enterprises are organisations, combining profit making with support of their employees and environment. Employee stress is harmful for both society (due to increased risk of mental health disorders and cardiovascular diseases) and for enterprise performance (due to increased risk of presenteeism, employee turnover and early retirement). This work aims at helping enterprises to improve employee wellbeing. To this end, we introduce a concept of IoT-based privacy-aware “team barometer” and present a first study into using inexpensive PIR (passive infrared) motion detection sensors in such barometers. The study was conducted as follows: first, we deployed IoT system in real offices and collected employee data in the course of everyday work during several months. Second, we developed a machine learning method to classify human conditions on the basis of collected PIR data. In the tests, this method recognised employees’ stress with 80% accuracy and dissatisfaction with indoor environmental quality - with 75% accuracy. Third, we integrated stress detection results into a “team barometer” and conducted interviews of line managers. Interview results suggest that the proposed IoT-based team barometer can be beneficial for both employees and enterprises because of its potential to discover and mitigate workplace problems notably faster than with current practice to use periodic surveys.

**Keywords:** stress detection, team barometer, PIR sensors.

## 1 Introduction

Recent social, economic and political challenges lead to the rise of so-called “social enterprises”: organisations, combining revenue growth and profit-making with respect and support of their employees, environment and stakeholder network [1]. This is not a matter of altruism: initiatives that have positive social impact are necessary for sustaining and growing businesses [2] and for attracting and retaining critical workers [1].

Reducing employee stress serves both goals of social enterprises: first, around 50% of all lost working days have some links with work stress [3], which is costly for society; and second, significant correlations exist between workplace stress, organisational commitment and organisational performance [4]. Currently, employers invest into reducing employee stress, but mainly by providing coaching/relaxation services. These services, unfortunately, do not eliminate underlying problems: work overload, time

pressure, lack of work variety, lack of control, unsatisfactory environmental conditions [5]. Indeed, a recent review of interventions to promote work participation of older workers (i.e., experienced workers over 45 years old) concluded that only combination of health services and work modifications improves work participation; there is not enough evidence to recommend health services alone [6].

Work modifications require involvement of managers; thus, managers should be aware of the problems. Typically, employee satisfaction/ dissatisfaction with workplace culture, own tasks, workload etc. is assessed via surveys, and individual answers to these surveys are aggregated into so-called “team barometers”: for example, they report average values of multiple answers. Surveys are usually infrequent, whereas 29% of new hires quit in 90 days: 45% of them - because day-to-day role was not what they expected, and 28% because of unsatisfactory company culture [7]. New tools to detect problems earlier are emerging, but they are based on explicit reporting of team members, for example, via email [8].

Modern technologies, such as Internet of Things (IoT) and data science, have a potential to detect problems in time and unobtrusively for the employees. Therefore technologies can help social enterprises to improve employee wellbeing and health. This study introduces the concept of IoT based “team barometers”, where IoT is used to collect human and environmental data, and intelligent algorithms are employed to assess human conditions on the basis of these data.

Technology-assisted assessment of human conditions is a relatively new research area; it started from analysis of video and physiological data. At work, however, video cameras rise privacy concerns. Physiological sensors are costly, and their data are affected by physical activities: in a recent large-scale real-life study stress detection accuracy was as good as random guess for 38% of test subjects [9]. Thus real-life stress detectors often utilise behavioural data, mainly, obtained from mobile phones [10] (e.g., application usage, locations etc.). This approach does not require any extra gadgets, but data collection may quickly drain phone battery [11].

In-office sensors do not require maintenance (e.g., charging) efforts from the monitored employees, and in-office motion detectors, such as depth cameras and PIR sensors, are usually well accepted [12, 13]. Motion features are also indicative of stress [12, 14, 15]. Currently, however, PIR sensors are mainly used for energy savings, whereas needs of users within the building are often ignored [13]. Furthermore, recently it was proposed to employ IoT to classify employees as high performers vs. low performers [16]. One of the features, derived from PIR data for the classification, was “higher performers spend more time at work during weekends”. This approach can be dangerous for employee health and detrimental for employers in the long term.

This work, on the contrary, presents a study into using IoT and PIR sensors for improving work satisfaction and wellbeing of employees. This work is organised as follows: Section 2 presents a concept of IoT-based team barometer. Section 3 describes IoT setup, used for collecting human data in the course of everyday office work. Section 4 presents a methodology to assess wellbeing of employees on the basis of collected data, along with the accuracies of data analysis results. Section 5 describes a methodology to aggregate results into team barometer and focus group study with line managers, conducted for evaluation of the proposed PIR-based team barometer.

The main contribution of this paper is introducing concept of IoT-based team barometer. To the best of our knowledge, this is the first real life study into using PIR sensors for assessing human stress and satisfaction with environmental conditions, and the first work, presenting a focus group study with IoT-based team barometer data.

## 2 IoT-Based Team Barometer

An overview of the proposed sensor data analysis-based team barometer is presented in Figure 1. The barometer relies on IoT nodes in the office cubicles to collect data, and on intelligent algorithms to assess individual conditions and to aggregate them into team states. Aggregated results are then visualised.

In this work, we recognise conditions of office workers on the basis of behavioural data, acquired from PIR sensors, and we aggregate recognition results over multiple individuals (to avoid privacy problems) and over time (e.g., couple of weeks). Aggregation over time is performed, first, because long-lasting problems are more likely to result in negative consequences for the individual (e.g., burnout) and for the organisation (e.g., resignation of a talented employee) than a short-term problem. Second, aggregation over time increases accuracy: for example, in [12] accuracy of classifying each day as stressful vs. normal was less than 70%, but accuracy of classifying months exceeded 90%. Last but not least, managers are also humans, they can be also stressed and hence do not want too detailed information.

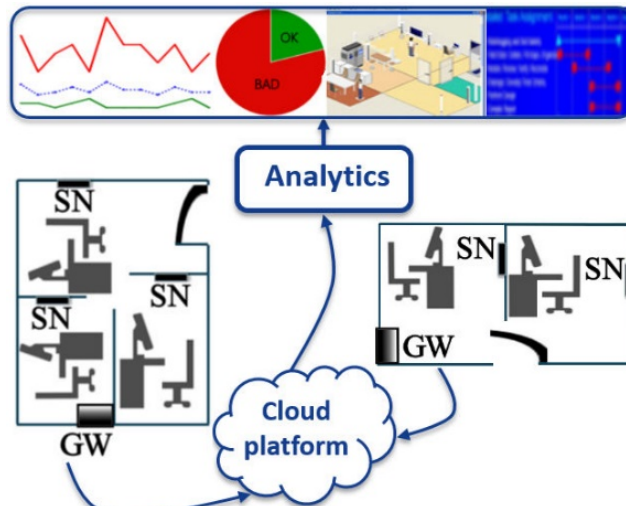
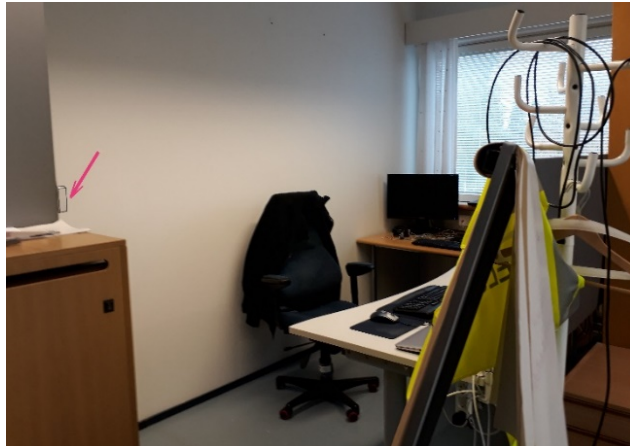


Fig. 1. System overview: SN - sensor node; GW - gateway.

### 3 Data Collection

#### 3.1 IoT setup

IoT-based system was deployed in our working premises to continuously collect sensor data. Figure 1 presents examples of IoT setup in three-person office and in two-person office, and Figure 2 presents a photo of an office cubicle and location of a sensor node (red arrow points there). In each cubicle, sensor nodes were positioned 1.1 metres above the floor level in a vicinity to a seating position (1-2 metres distance). This way, each sensor node was monitoring a single individual, but motion detection was robust to changes in his/ her positions inside the office cubicle: for example, Figure 2 shows that the monitored subject had two computers and was moving between them.



**Fig. 2.** Sensor placement in the office cubicle

In this study, we use Tiny Sensor Node [17] with Panasonic EKMB1301113K PIR sensor [18]. It acquires 12 samples per minute; every single sample can take either value 0 (no motion) or value 1 (motion detected). Tiny Sensor Node aggregates these values over one minute (aggregated values range from 0 to 12) and sends them over Bluetooth Low Energy to the data acquisition gateway application, running on a Raspberry Pi computer. The gateways send data to Microsoft Azure cloud platform via MQTT protocol over TCP/IP.

Data retrieval from Azure utilises a published API for Microsoft Azure Table Storage. We implemented a client application, based on Cosmos DB API, which provided an interface to TableStorage via a module, called TableService [19]. Data were retrieved periodically in batches.

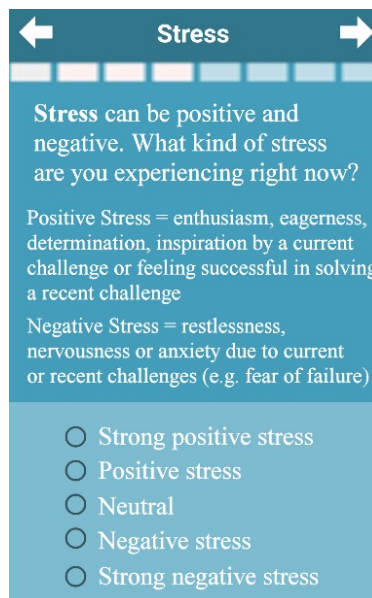
#### 3.2 Collection of Self-Reports

Self-reports of the monitored subjects were collected on 5-point Likert scale via mobile phone application, developed for Android phones. Figure 3 presents a screenshot of

stress-related part of the application. Other questions, used in this study, were formulated as follows:

- How productively did you work today? Options to answer: (a) much more productively than usually; (b) more productively than usually; (c) as usually; (d) less productively than usually; (e) much less productively than usually.
- How would you estimate air freshness at the moment? Options to answer: (a) very good; (b) good; (c) acceptable; (d) bad; (e) very bad.
- How would you estimate temperature at the moment? Options to answer: (a) cold; (b) cool; (c) neutral; (d) warm; (e) hot.

Questions regarding air freshness and thermal comfort were asked two times on each workday (morning and afternoon); questions about stress and productivity were only asked in the afternoon. Answers were stored in MongoDB and retrieved via REST API.



**Fig. 3.** Screenshot of stress-related part of self-reporting application.

### 3.3 Dataset

For this study 30 subjects were recruited, but in the middle of data collection part of the subjects was relocated because renovation started in their offices. The renovation started because of unsatisfactory air quality, which is a good sign: it shows that aggregated opinions of employees can influence working conditions. Unfortunately, relocations and several other drop-outs (e.g., one subject fell ill, another one started to work on PhD elsewhere etc.) reduced number of subjects, whom from self-reports were obtained in sufficient quantities: for analysis of thermal comfort and air quality we used data of 15 subjects (they were mainly middle age researchers, 7 females and 8 males).

For analysis of stress and productivity perceptions we used data of 6 persons (2 females and 4 males) because stress- and productivity-related questions were asked only once per day; hence, data size for these questions was approximately twice smaller.

## 4 Data Analysis

Stress-induced motion changes are distinct to every individual (for example, some individuals sit still during difficult tasks, and some fidget [15]), and person-specific models of stressed behaviour usually achieve 20% higher accuracies than “one-fits-all” models [14, 15, 20]. Perception of thermal comfort and air quality, as well as physical reactions at them, are also person-dependent. Therefore, we employed person-specific models in this study. To date, the majority of existing stress detectors were trained in fully supervised way [10], and thermal comfort models too [21]. Thus in this study we also used supervised classifier - SVM (Support Vector Machines). As class labels we used subjective perceptions of the test subjects because it is a common practice: it is not possible to obtain objective measures of human conditions in everyday work. We have chosen SVM because human behaviours vary a lot, self-reports may contain mistakes, and SVM is a noise-robust classifier, capable of learning from relatively small datasets. We used SVM implementation in scikit-learn Python library. We used sigmoid kernel with its default parameters, but with twice higher penalty for misclassifying examples of “bad” class because there were fewer examples of this class in the data.

For feature extraction we used tsfresh Python library; it extracts over 300 data features (for descriptions see [22]). Feature selection was performed by calculating correlations between every feature and respective class labels (e.g., correlation between “energy” feature values and stress labels, correlation between “energy” feature values and productivity labels etc.). Thus we selected best features for each problem separately.

Although self-reports were collected on 5-point Likert scale, their quantity was sufficient only to train 2-class classifier. Hence in this study we distinguished between “bad” and “OK” conditions. For stress detection “bad” class included “negative” and “very negative” self-reports, while “OK” class included “neutral”, “positive” and “very positive” self-reports. Similarly, for productivity classification “bad” class included “much less productively than usually” and “less productively than usually” answers, while “OK” class - all other answers. For air/ temperature perception “bad” class included “bad” and “very bad” answers; “OK” class included all other answers. This approach resulted in the following percentages of answers of “bad” class in the data: stress - 28%; productivity - 18%; air freshness - 45%; thermal comfort - 51%.

Then, SVM was trained to map sensor data into one of the two classes of personal perception: for example, to classify stress self-report into either “bad” or “OK” class.

### 4.1 Experimental Protocol

Since data were not abundant, for each test subject we used leave-one-self-report-out protocol: first, one self-report and the corresponding sensor data were selected as test data, and all remaining data were used for feature selection and SVM training. Then

this process was repeated for all self-reports of this person, and then the same procedure was repeated for all other subjects. For each subject, we trained a separate SVM model for each question. Sensor data features were extracted from time windows, preceding each self-report in training data (we used time window length two hours).

For testing, we extracted selected features from the test data, classified each test sample with SVM and compared SVM output with the corresponding self-report. We estimated test accuracy according to the following measures:

$$Total\ Accuracy = \frac{N_{correctBad} + N_{correctOK}}{N_{bad} + N_{OK}} \quad (1)$$

$$True\ Bad = \frac{N_{correctBad}}{N_{bad}} \quad (2)$$

$$True\ OK = \frac{N_{correctOK}}{N_{OK}} \quad (3)$$

In the equations (1), (2) and (3)  $N_{correctBad}$  is the number of correctly classified “bad” answers;  $N_{correctOK}$  is the number of correctly classified “OK” answers,  $N_{bad}$  and  $N_{OK}$  are numbers of “bad” and “OK” answers, respectively.

## 4.2 Classification Accuracies

Table 1 presents classification accuracies, obtained from PIR data.

**Table 1.** Classification Accuracy.

Problem	Total accuracy	True OK (True Negative)	True bad (True Positive)
Stress	0.80	0.86	0.60
Thermal comfort	0.75	0.72	0.80
Air freshness	0.75	0.70	0.80
Productivity	0.70	0.92	0.25

Table 1 shows that the employed classification approach results in reasonably high accuracies (considering coarseness of PIR-based motion data) for all questions except for productivity. The proposed approach was not able to detect practically any case of perceived low productivity. We consider this result good, too, because it means that the employer cannot use such system for assessing employee performance; instead, the employer should invest efforts into keeping the employees healthy, happy and motivated.

## 5 Focus Group Study

### 5.1 Visualisations of Data Analysis Results

Figure 4 presents one of the proposed team barometer views: a plot of weekly team states for 12 weeks, created using stress detection results of all test subjects (for some subjects we did not have data for longer time period). Vertical axis in Figure 4 presents

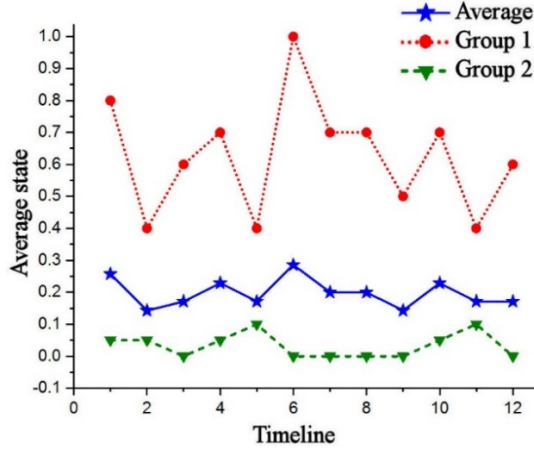


a stress score, calculated as follows: first we obtained stress detection result for each day as described in the previous section, then calculated a week score of each subject according to equation (4), and then averaged the scores over the subjects.

$$Score = \frac{1}{N} \sum_{i=1}^N ClassifierDecision_i \quad (4)$$

In equation (4),  $N$  is number of days in the corresponding time interval, for which classifier decision was obtained.  $ClassifierDecision_i$  is SVM output for test sample number  $i$ . It takes value 1 if SVM classifies the day into “bad” class, and value 0 if SVM classifies the day into “OK” class. Accordingly, average score of a time interval ranges from 0 (all days were classified as “OK” days) to 1 (all days were classified as “bad” days).

Horizontal axis in Figure 4 presents interval number. In Figure 4, interval is one week, but we don’t display it in the figure legend because for the focus group study we needed unspecified time interval.



**Fig. 4.** Stress detection results, averaged over weekly intervals and test subjects. “Average” plot presents average over all test subjects; “Group 1” and “Group 2” plots present averages over the most stressed one/ third of the subjects and the least stressed one/ third of the subjects respectively

Figure 4 shows that subjects in the two groups experienced stress at different times (e.g., results for weeks 5 and 11 are negatively correlated), possibly due to differences in work tasks. Figure 4 also shows that Group 1 experienced higher stress, either due to differences in work tasks or personalities or both.

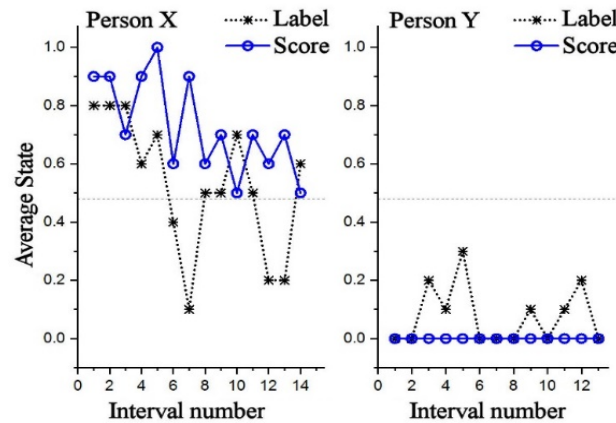
Figure 5 presents stress detection results, averaged over two-weeks-long time intervals, and corresponding averages of self-reports for two test subjects. They were selected because they were very different (Person X was stressed much more often than Person Y) and because stress detection errors for them look impressive. For Person X, Total Accuracy is 0.70 (True OK = 0.42; True Bad = 0.80); for Person Y, nearly none of self-reported stress cases were detected.

Average score for each interval in Figure 5 was calculated according to equation (4), and average label was calculated according to equation (5).

$$Label = \frac{1}{N} \sum_{i=1}^N BinaryLabel_i \quad (5)$$

In equation (5),  $N$  is number of days in the corresponding time interval, for which classifier decision was obtained, and  $BinaryLabel_i$  is a discretised self-report for sample  $i$ . It takes value 1 if “bad” or “very bad” stress was reported, and value 0 otherwise. Accordingly, average labels for biweekly period range from 0 (all days were reported as “OK” days) to 1 (all days were reported as “bad” days).

Figure 5 shows that the proposed PIR-based stress detector over-estimated number of stressful days of Person X and under-estimated number of stressful days of Person Y. The main reason is great variety of tasks and motion behaviours: e.g., classifier results were influenced by absences from the office and by numbers of visitors (communication with them typically involves more motion than typing on a computer). Detection errors for Person Y were also due to his/ her imbalanced data: number of examples of “OK” class notably exceeded number of examples of “bad” class. Nevertheless the overall conditions were estimated reasonably well.



**Fig. 5.** Stress classification results and self-reports for two test subjects, averaged over bi-weekly intervals. Dotted line separates difficult periods from easier ones: if a person is stressed on more than 50% of days, this period is definitely not easy.

For person X Figure 5 presents results for 14 biweekly intervals, which corresponds to 140 days in the office; for person Y - for 13 biweekly intervals, which corresponds to 130 days in the office.

## 5.2 Study Protocol

We conducted face-to-face interviews (as a free-form discussion) with 8 individuals: one representative of a trade union and 7 subjects who held managing positions for at least a year. Each interview lasted about 30 minutes. Four of the interviewed persons had about 30 subordinates; three of them had 100 and more subordinates. In the beginning of each interview we described IoT solution and Figure 4. We explained that Figure 4 is a graph of stress detection results in an organisational unit, presenting (1) an average over all monitored subjects; (2) the most stressed subgroup; (3) the least stressed subgroup. Then we asked the following questions:

Q1: let's assume that this system is working in your unit; what would you do when you see these results?

Q2: how would you see forming of "group 1", "group 2" etc.: for example, split can be by stress levels, by work tasks/ positions/ organisational units, or in some other ways?

Q3: what kind of timeline (interval size) do you envision: weekly, bi-weekly, monthly, anything else?

Q4: we can make similar graphs for thermal comfort and comfort with air quality, what would you do with them?

Then we presented Figure 5, explained how scores and labels were calculated and pointed out the discrepancies between scores and labels. After that, we asked:

Q5: as you see, the system is not accurate, what do you think about its inaccuracy, and how would you take it into account?

### 5.3 Results

Answering to Q1, all managers started from workload distribution and task assignment problem, but they approached it from different directions. Their answers largely fall into two groups: "happier workers work better" and "unhappy workers do not work well". That is, managers in the first group believe that attention to conditions of their subordinates would pay off in a long term in a form of higher motivation and improved workability. Managers in the second group prioritise current organisational performance. They want to give every task to a person who is the best fit for this task, and they believe that an already overloaded/ stressed person cannot be "the best fit".

Both types of managers stated that they are ready to help stressed persons by contributing themselves to a difficult task or by temporarily allocating more resources to this task, but managers of the second type were more inclined to delegate the problem of long-lasting stress to occupational health therapists than managers of the first type.

Managers of the first type appeared to be well prepared to deal with anonymous graphs: they all stated "if the system signals a trouble, I'll go and talk to people". These managers were also interested to find stress reasons: they suggested augmenting team barometer with contextual information, such as various deadlines, company announcements etc., to improve planning (e.g., to start certain tasks earlier). In addition, a high-level manager said that if some group is constantly more stressed than the others, he would investigate whether leadership style causes problems.

Managers of the second type were more interested in getting lists of persons who are "able to take a new task now" and "who needs help now". This approach is difficult (if possible at all) to realise in a privacy-safe way. These managers were not expecting subordinates to work in any condition, however. Thus team barometer could be designed also to recommend stressed individuals to seek managers' support.

Answering to Q2, managers of the first type approved team split as "worst stressed group" vs. "least stressed group" and emphasised importance of checking conditions of "the worst stressed" group periodically - to see trends. They also said that if a new "worst stressed group" will form meanwhile, team barometer should also show it. Managers of both types suggested to split groups also by work tasks: they said that this split

would help to provide timely support to “the task in trouble”. Other suggestions were (1) to split groups according to work challenges (when work requires more novelty/creativity, it needs more attention from a manager) and (2) to split groups by demographic factors, like age. One manager, however, said that since he anyway would need to go and talk to people, any kind of indication that problem exists would suffice.

Regarding Q3, the majority of the managers had similar opinions: if stress lasts longer than a month, it is at least a first checkpoint. Being stressed for a month before a major deadline is a common case, but after that trends need to be monitored. And if stress lasts longer than two-three months, then manager’s help would be definitely needed. Managers could not say, however, how exactly timeline in team barometer should look like (e.g., week, two weeks or a month) - they suggested testing different views in long-term use. Managers of the second type were more confident: they expressed interest in checking team barometer on a weekly basis in cases when tasks are more challenging than usually or when stressed group is likely to include people whom they don’t know well.

Answering to Q4, most of the managers stated that it’s easy to move the employees around until everybody is happy: for example, employees can be co-located based on similar preferences for thermal comfort and ventilation.

Answering to Q5, managers of the first type said “technology is just an indicator, I’ll need to go and talk anyway”, and “tools, based on explicit reporting, are not highly accurate either”. Managers of the second type wanted to get as accurate actionable information as possible at least with respect to readiness to take a new task, but nobody expected any barometer to be 100% accurate.

Representative of a trade union said that team barometer could help to discover workload distribution problems and leadership problems: if for example three persons in a team have high stress level for more than a month, it is a reason to go and talk to the team. He also said that he would check average team states on monthly basis unless somebody comes and complains; then more frequent checks would be needed.

## 6 Conclusion

Skilful, motivated and healthy workforce is a key to enterprise success, that’s why recently the term “human capital” started to supersede the term “human resources” and that’s why employee wellbeing emerges as a strategic priority of enterprises [23]. This work presents a first study into using IoT for improving wellbeing of office workers.

In this study we deployed inexpensive PIR sensors in real office cubicles, collected motion data of the monitored subjects and developed machine learning method to access subjects’ conditions. We consider use of real-life data very important because the majority of previous studies into use of motion data for stress detection took place in the labs. Lab studies typically last only a few hours under assumption that a short-term high mental workload is equal to stress. Furthermore, in lab studies stressful tasks typically alternate by periods of relaxation. In real life, however, tasks can last long, and frequent periods of relaxation are not possible. Therefore stress does not display itself in human behaviour in real life in a same way as in the labs [12].

The main advantage of employing in-office sensors is their unobtrusiveness, and the main drawback - ability to evaluate employees' conditions only when they are in their offices. This is not crucial, however, as the most dangerous stress type is chronic stress: long-lasting stress of low intensity may have equal or greater health impact than short-term high intensity stress [24]. Therefore team barometer does not need to detect stress on daily basis; detecting long-lasting stress would suffice, and interviews with line managers support this approach. Team barometer can employ also other sensor types, if the system is privacy-safe and unobtrusive.

The main limitations of this study are small number of test subjects and that all interviewed managers were from research organisation. Stress is an important health problem also for researchers, however [25]. In addition, growing competition for talented workers and consequent rise of "social enterprise" start influencing work culture in companies [23]. In future, we plan to collect more data and to test team barometer in the course of everyday work in teams of most trustworthy managers, to discover potential privacy threats, to develop privacy safeguards and to give employees control over the system. We also plan to compare various visualisation approaches.

We consider results of this work encouraging for future studies into using IoT to improve work satisfaction, motivation and wellbeing of the workforce because none of the interviewed managers said "stress of my subordinates is not my problem", and nobody expressed any intention to start a blame game based on technology reports. Instead, the managers said that the proposed team barometer is a good indicator of problems and could therefore help to improve work conditions and that they need to talk to their subordinates before taking any action.

## References

1. 2018 Deloitte Global Human Capital Trends, [https://www2.deloitte.com/content/dam/insights/us/articles/HCTrends2018/2018-HCtrends\\_Rise-of-the-social-enterprise.pdf](https://www2.deloitte.com/content/dam/insights/us/articles/HCTrends2018/2018-HCtrends_Rise-of-the-social-enterprise.pdf), last accessed 06.07.2020
2. Success personified in the Fourth Industrial Revolution, [https://www2.deloitte.com/content/dam/Deloitte/global/Documents/gx-davos-DI\\_Success-personified-fourth-industrial-revolution.pdf](https://www2.deloitte.com/content/dam/Deloitte/global/Documents/gx-davos-DI_Success-personified-fourth-industrial-revolution.pdf), last accessed 06.07.2020
3. Cox, T., Griffiths, A., & Rial-González, E. (2000). Research on work-related stress. Luxembourg: European Agency for Safety and Health at Work.
4. Karacsony, P., Examining the Relationship Between Workplace Stress and Organizational Commitment, MSIE 2019, pp. 26-30.
5. Michie, S., Causes and management of stress at work, *Occupational and Environmental Medicine* 2002, 59: 67-72
6. Steenstra, I., Cullen, K., Irvin, E., Van Eerd, D., A systematic review of interventions to promote work participation in older workers, *J Safety Res.* 2017 60: 93-102
7. 2019 Job Seeker Nation Survey, [https://www.jobvite.com/wp-content/uploads/2019/04/2019\\_Job\\_Seeker\\_Nation.pdf](https://www.jobvite.com/wp-content/uploads/2019/04/2019_Job_Seeker_Nation.pdf), last accessed 06.07.2020
8. Team mood, <https://www.teammood.com/en/>, last accessed 06.07.2020
9. Smets E., Velazquez, E. R., Schiavone, G., Chakroun, I., D'Hondt, E., De Raedt, W., Cornelis, J., Janssens, O., Van Hoecke, S., Claes, S., Van Diest, I., Van Hoof, Ch., Large-scale

- wearable data reveal digital phenotypes for daily-life stress detection, *npj Digital Medicine* volume 1, Article number: 67 (2018)
10. Alberdi, A., Aztiria, A., Basarab, A., Towards an automatic early stress recognition system for office environments based on multimodal measurements: a review, *Journal of Biomedical Informatics* 59 (2016), 49-75
  11. Muaremi, A., Arnrich, B., Tröster, G., Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep, *BioNanoScience* 2013, 3(2), pp 172-183
  12. Vildjiounaite, E., Huotari, V., Kallio, J., Kyllönen, V., Mäkelä, S.-M., Gimelfarb, G., Unobtrusive assessment of stress of office workers via analysis of their motion trajectories, *Pervasive and Mobile Computing*, Volume 58, 2019
  13. Jia, M., Komeily, A., Wang, Y., Srinivasan, R.S., Adopting Internet of Things for the development of smart buildings: A review of enabling technologies and applications, *Automation in Construction*, Volume 101, 2019, Pages 111-126
  14. Garcia-Ceja, E., Osmani, V., Mayora, O., Automatic Stress Detection in Working Environments from Smartphones' Accelerometer Data: A First Step, *IEEE Journal of Biomedical and Health Informatics* 2016
  15. Koldijk, S., Neerinx, M.A., Kraaij, W., Detecting work stress in offices by combining unobtrusive sensors, *IEEE Transactions on Affective Computing* 9 (2) pp. 227-239, 2018
  16. Mirjafari, Sh. et al. Differentiating Higher and Lower Job Performers in the Workplace Using Mobile Sensing. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 2, Article 37 (June 2019), 24 pages
  17. VTT Sensor Node, <https://www.vttresearch.com/en/ourservices/energy-autonomous-wireless-sensor-networks#search=tiny%20node>, last accessed 06.07.2020
  18. PIR sensor, <https://na.industrial.panasonic.com/products/sensors/sensors-automotive-industrial-applications/lineup/pir-motion-sensor-papirs/series/70516/model/73542>, last accessed 06.07.2020
  19. Azur table, <https://docs.microsoft.com/en-us/python/api/azure-cosmosdb-table/azure.cosmosdb.table.tableservice?view=azure-python>, last accessed 06.07.2020
  20. Maxhuni, A., Hernandez-Leal, P., Sucar, L.E., Osmani, V., Morales, E.F., Mayora, O., Stress modelling and prediction in presence of scarce data, *Journal of Biomedical Informatics*, 63 (2016) 344-356
  21. Peng, Y., Nagy, Z., Schlüter, A., Temperature-preference learning with neural networks for occupant-centric building indoor climate controls, *Building and Environment*, Vol. 154, 2019, pp. 296-308
  22. tsfresh library, <https://buildmedia.readthedocs.org/media/pdf/tsfresh/latest/tsfresh.pdf>, last accessed 06.07.2020
  23. Well-being: A strategy and a responsibility, <https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2018/employee-well-being-programs.html>, last accessed 06.07.2020
  24. Lamb, S., Kwok, K.C.S., A longitudinal investigation of work environment stressors on the performance and wellbeing of office workers, *Applied Ergonomics* 52 (2016) pp. 104-111
  25. C. A. Stewart and M. Krefeldt, Your Good Health is a Workforce Issue, In *PEARC '18*, Article 4, 8 pages