R. Zender, U. Lucke, J. Haase, M. von der Heyde, G. Leitner und W. Meyer (Hrsg.):
Proceedings des Workshops "Lernen und Arbeiten im Wandel", Potsdam, 2018 44

Towards the Empathic Building - Detection and recognition of well-being of individuals and groups

Jan Budke[1], Mario Cichonczyk[1] and Dominic Becking[1]

Abstract: This paper reviews the current state of science and technology on the detection and recognition of well-being of individuals and groups of people. It turns out that most of the current research projects refer merely to partial areas of this problem. Some concentrate on single values like temperature, ventilation or lighting separately. However, the results are often encouraging, suggesting that recognition of general well-being could in principle be possible. Based on these results, we propose a new approach to measure and detect complacency in order to enable smart buildings to react to the needs of the inhabitants and users accordingly. Datasets composed of personal data from portable sensors and wearables or from questionnaires, data from sensors of the building and additional information like the current utilization of the room result in a clustering problem which can be solved using methods and algorithms of supervised learning.

Keywords: well-being, comfort, machine learning, smart building, building automation

1 Introduction

Buildings account for 40% of total energy consumption in Germany. Functional buildings make up less than 10% of the total number of buildings, but they use 40% of the primary energy consumption of all buildings [Bi12]. The greatest potential for improving the energy efficiency lies therefore in the restoration and modernization of the stock. This is one reason why many functional buildings are equipped or upgraded with building automation and smart technologies [WHHB15].

Another reason is to improve the working and living environment of the inhabitants and users of such buildings. One goal is to relieve users of menial tasks such as turning on the lights. In functional buildings, this often leads to situations in which users are confronted with technologies they did not choose to use and which, in some cases, they have difficulties to influence or take control of [WHHB15]. In these situations, it is likely that users do not accept certain technologies. It is often observed that users avoid them or actively cause sensors to detect false signals or values. This way users override the benefits of these technologies or even reverse them resulting in increased energy usage and higher costs. The more complex said technologies get, the higher is the risk of users rejecting it [RUU10b].

[1] University of Applied Sciences Bielefeld, Institute for the Intelligent Building, Ringstraße 95, 32427 Minden, Deutschland, firstname.lastname@fh-bielefeld.de

Building automation is also often governed by standards and fixed default values. Other influencing factors, direct or indirect, are therefore neglected. By looking at the individual situation, it should be possible to save more energy and reduce costs while improving the work and life situation of the users and residents at the same time.

These are the main reasons why we propose a system which enables smart building technology to react according to several different influencing factors related to the well-being and complacency[2] of users, resulting in an empathic building.

In the current situation, residents and users of buildings have to manage many things manually. In larger rooms, several thermostats must be operated to adjust the heating/cooling, there are several switches to control and dim the various light sources, windows must be opened and closed individually. At the same time, we are dealing with a very inert system in which changes can only be achieved relatively slowly. As a result, the user may feel uncomfortable or his/her work performance is impaired (e.g. by cold/heat, too weak or too strong lighting, etc.).

With the current state of knowledge, we define the **Empathic Building** as a living and working space that automatically adapts to the needs of one or more residents or users. In doing so, basic needs as well as preferences of individuals and groups of persons should be considered. These should be learned without user intervention, so that manual configuration is no longer necessary.

In this paper we provide an overview of the current state of the scientific and technical knowledge with regard to our project. Based on this literature review, we will propose our idea in detail and elaborate on the next steps.

2 Related Work

2.1 Acceptance

Usability and acceptance have a common area of overlap but also need to be taken into consideration separately since there seems to be no direct interdependency. Products with a good usability can also be rejected by the users [De13]. If a product is rejected by users, psychology explains parts of this reaction as reactance behavior. According to Brehm, a person reacts with resistance if they feel that their freedom is restricted or threatened [Br72].

This can be interpreted as the restriction of (degrees of) freedom. This restriction of degrees of freedom can be divided into three categories. For the scenario with the intelligent building at the center of interest, the narrowing of freedom due to environmental conditions is of great importance. This means in general that certain

[2] Well-being refers to the physical factors and complacency to the psychological factors.

requirements, laws, scarcity or similar factors cause that a decision-making alternative is no longer available. This type of constraint is of particular importance for the discussed subject, since the technologies of intelligent buildings often require a certain rethinking. Regularly, familiar behavior patterns of users have to change because functions are implemented differently or have been taken over by the building control. For example, the way in which windows are opened, blinds are closed or the lights are controlled [RUU10a].

Since reactance is motivated by the urge to restore threatened or lost liberties, this also means that it is not directly observable [RUU10a]. Therefore, a distinction must be made between reactance and reactance effects. There are several classes of reactance effects, but the most important one for this subject is *the direct restoration of freedom*. In this case, a familiar means of interaction is no longer supported or offered. The person showing reactance tendencies tries to take this alternative anyway, although this behavior might be sanctioned. However, the threat of this sanction is too weak to make the proposed alternative attractive enough.

Ehrenbrink, Hillmann, Weiss and Möller [Eh16] performed a study that analyzed self-adaptive and user-adaptable systems and compared their effects on users' reactance while interacting with a dialogue system. *Hong's Psychological Reactance Scale* and an ensuing factor analysis was used for the questionnaire. The resulting findings show that interaction with self-adaptive systems compared to user-adaptable systems can increase reactance.

In this context, another paper is interesting and should be mentioned: Heine, Buhr, Eschweiler and Weimar [He16] focus their work on the challenges of our ageing society and try to improve user involvement of elder end users in smart environments in order to create a better acceptance. Therefore, a living lab called 'LebensPhasenHaus' was established, where users can experience different smart systems and the main purpose of this house is to raise awareness and inform elder people. The results show that the elder users were comfortable with the system and after a while they explored the system on their own, adapting the environmental parameters according to their needs.

2.2 Temperature and Thermal comfort

The standard specification ISO 7730:2005 states that there are six parameters for human thermal comfort: air temperature, radiant temperature, humidity, air speed, clothing level and activity level [IO05].

Early on, several researchers have shown dependencies between performance capability and room temperature. Furthermore, in the work of Wyon, Andersen and Lundqvist [WAL79], this performance reduction was quantified for the first time. In one example for seated activity, light clothing and a room temperature of 26°C, a performance reduction of 13% compared to a temperature of 23°C can be expected. At the same time, memory performance increases substantially while the temperature rises from 23°C to

26°C, henceforth decreasing again with rising temperature. In practice, complaints are expressed regularly although technical measurements stay in a zone where the highest level of comfort should be. Obviously, the perceptions of some users do not correlate with the recommendations derived from said research. Fiedler argues that these feelings are strongly dependent on individual factors and preferences and that they are not generally the same for all people [Fi16]. However, he confirms that temperatures between 20°C and 25°C are usually desired in individual offices and between 22°C and 24.5°C in open-plan offices.

The results of [CL12] suggest that the surface temperature of the hand provides meaningful values. In some cases, additional sensors at other parts of the body provide useful data which at the same time limit the user's personal freedom. In a study by Choi and Loftness the skin temperature was used to adjust the room temperature. Skin temperature was measured at different parts of the body and the data was analyzed to assess a correlation between skin temperature and comfort. The results showed that the temperature differences and the changes of temperatures had a much stronger effect than the actual current values. The researchers also found that the measured skin temperatures at the wrists provided data which could be interpreted better than that of any other body segments. This data allowed to distinguish even two closely neighbored sensations like slightly warm and neutral.

Furthermore, it could be shown that people who have the notion that their influence on the indoor climate is high estimate their productivity higher as those with a low perceived possibility of influence and control [LB99]. In conclusion, the facility management of a building has a direct and indirect effect on the productivity of people working in it. Contrary to these findings, most commercial buildings use fixed settings. Zhang, Lam and Wang [ZLW14] in contrast focus their work on the idea that participatory building management systems provide a better energy efficiency while at the same time offering greater thermal comfort. It is crucial for these occupant-participatory approaches that the occupants are trustworthy and do not lie to the system by giving false feedback. In order to achieve this trustworthiness, they propose a strategy-proof framework for thermal comfort voting schemes.

2.3 Air Quality

In recent years, the topic of air quality has drawn considerable attention due to increasing problems with air pollution in big cities. Many research projects deal with the monitoring of air quality (e.g. [Ki13]). People spend a lot of their time (nearly 90% [EP04]) indoors and therefore good indoor air quality has an effect on our comfort and is a vital part of human health. For this reason, some research activities concentrate on the measurement, visualization and improvement of air quality in buildings. For example, Frešer, Gradišek, Cvetković, and Luštrek [FGCL16] state that in addition to thermal comfort, air quality affects the productivity of employees. They designed a system which monitors temperature, humidity and CO_2 concentration and detects whether the windows are opened or closed. They combine this data with a self-designed ontology to recommend actions via a smartphone application to users. For the implementation of the predictive functions, different regression algorithms were tested and the Support Vector Regression provided the best results and was selected. The system was evaluated and it was shown that the occupants comfort was improved.

Kim and Paulos [KP09] work is based on air quality being difficult to rate without measurements since it cannot be detected through sight and smell. They developed a system called 'inAir' to solve this problem by measuring and visualizing these parameters in such a way that also non-scientists are able to understand. Their software creates historical and real-time visualizations of the data from different sensors. These charts are displayed in an iPhone-App. The system was validated in a two-week study with five private households which proved the relevance of their work showing that these visualizations were considered helpful. Min, Forys and Schmid [MFS14] follow a similar approach. They developed 'AirFeed', an interactive air quality monitoring system for indoor use. The system detects particles, humidity, and temperature and sends measurements to a server which analyzes this data after combining it with regional information and user feedback (see figure 1). One result from their ongoing work is the successful mapping of human activities to different levels of air quality. The amount of experimental observation is not yet sufficient and a more extensive evaluation will be needed.

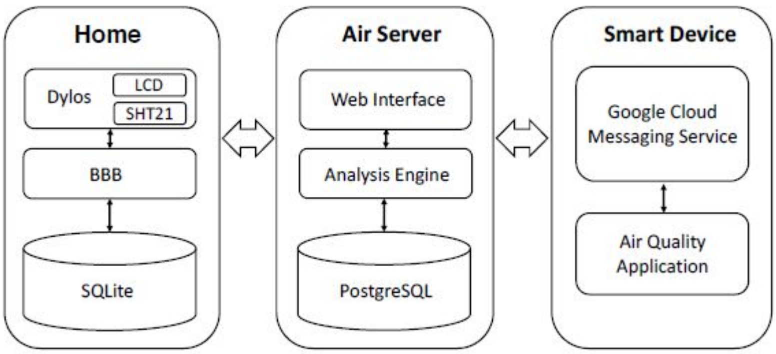

Fig. 1: The AirFeed System Architecture [MFS14]

The paper by Snow, Soska, Chatterjee and Schraefel [SSCS16] should also be mentioned in this context, since it provides a social perspective to the topic of air quality in naturally ventilated office environments. They performed 15 qualitative structured interviews, asking about social factors of opening windows and doing thermostat adjustments in shared offices. They found that social factors affect behavior in such a way that some people accepted sub-optimal conditions (too hot, too cold) in order to avoid discussions and arguments.

2.4 Mood Recognition

There already are some interesting research projects regarding the subject of mood recognition whose results could at least partly be used for the establishment or improvement of an empathic building. For example, LiKamWa Liu, Lane and Zhong developed a system called 'MoodScope' [LLLZ13], a mood sensor based on smartphone usage. The user was asked about his mood 4 times a day and the answers were matched with an automatic recognition done by the system at the same time. To predict the daily average mood, they used multi-linear regression and sequential forward feature selection. MoodScope was tested collecting two months of usage data and self-reported mood provided by 32 participants. The results validate their approach, although they admit that *'not every factor that impacts user mood can be captured by a smartphone'* [LLLZ13]. One problem with this approach was that the user was questioned at fixed intervals and not dependent on the current situation or in an adaptive way. Also, the *average mood* does not account for immediate situations. Another problem was the insufficient anonymization of data.

Additionally, Bachmann et al. [Ba15] focused their work on the aspect of how to use smartphones for less obtrusive mood recognition. In their paper, they describe a smartphone app that can be used to measure the mood, fatigue and stress of a user. They designed the system in order to use it in the context of health care, e.g. for the monitoring of patients. Based on first measurements, they analyzed which features provide the best recognition results and showed that space-time attributes, such as daytime, weekday and place provide the most information about fatigue and stress and can be measured easily. They also found a correlation between high fatigue or stress and poor mood.

With the help of this app, they did a formative user study with nine persons in order to validate the usability of the system and to get training datasets with additional self-reports. For example, the app asked for the user's mood using Likert scaling[3] after certain events occurred (e.g. message received/sent, call finished) but they tried to avoid too many notifications at the same time. Then the classifiers used for mood-, fatigue-, and stress-recognition were trained with naive Bayes and ten-fold cross-validation. Overall, this gave an accuracy of 76% and after the heart rate was additionally included, the detection rate could be increased further. As a final advice, Bachmann et al. [Ba15] recommend other researchers to try out different algorithms and then determine features and classifiers.

Exler, Schankin, Klebsattel and Beigl [ESKB16] also worked on the topic of mood assessment. In their approach, they combined smartphone based self-reports, a smartwatch and a wearable ECG monitor. Thus, this enabled them to collect subjective feedback and objective body data at the same time. Their research shows that mood and biophysical reactions of the human body correlate and that, in addition to heart rate, the

[3] The Likert scale is a method for measuring personal attitudes. Respondents specify their level of agreement or disagreement on an agree-disagree scale for a series of statements.

temporal aspect is also of great importance. Decision trees were trained during three weeks of usage and then tested showing a high recognition accuracy (up to 91%). It can be said that the app they created and the combination of smartphone and smartwatch is in principal a suitable approach for mood recognition. However, they already have several plans for future enhancements, like noise level recognition, an ambient light sensor and the correlation with the user's location (shop, restaurant, office).

Niforatos, Elhart and Langheinrich [NEL15] created an app on four interactive touch-enabled public displays on a university campus in order to gather information on well-being of students (see figure 2). In their approach they measure the heart rate of bypassing students with a camera-based estimation and combine results with answers of some self-reporting questions. At the time being, their work is merely a position paper, describing ideas and research questions but no validated results are shown yet. For the future they plan to work on this topic and answer some questions regarding heart rate variation during a student's day, specific periods of increased heart rate and whether students perceive the measurement as rather useful, playful or disturbing.

Fig. 2: Prototype for mood recognition app by Niforatos et al. [NEL15]

2.5 Combined Factors & Machine Learning

Carreras, Higuera, Perálvarez and Hertog [CHPH14] created a new smart lighting and climate system by analyzing different comfort indicators. Their system was based on two components: the intelligent light engine and the smart thermostat. The intelligent lighting engine was able to detect natural light levels and adjust the artificial light sources to increase the visual comfort and reduce energy costs. The smart thermostat included a sensor and actor system to monitor users, temperature, air velocity, CO_2, relative humidity and illuminance levels. By adjusting comfort indicators, the system allowed to reduce the energy consumption up to 23% in lighting and 43% in HVAC. The authors used input variables like occupancy user detection, daylighting levels, the position of the blinds, the schedule of work and the daylighting indexes. The thermostat also calculated two thermal comfort indicators to predict the satisfaction of a group of people. They are, however, not based on data generated by the users themselves.

The importance of user participation in smart building technology is shown by the research of Harfield and Rattanongphisat [HR17]. They presented an alternative to plain building automation with a monitoring platform that empowers users to make intelligent decisions about energy efficiency. Their system used temperature, humidity, power and occupancy information to provide users information on how to reduce energy consumption. The evaluation showed that by analyzing the collected data, areas with potentially high energy savings could be identified. The authors also pointed out that reacting to users leads to better energy savings than full automation.

3 A New Approach

The idea for the system proposed in this paper arose from a subjective impression most public speakers can relate to. People like lecturers in universities develop a sense of or a connection to the mood of their audience. Standing in front of a crowd, it is often subjectively possible to assess if this group of people is for example relaxed, alert, tired or stressed. If a human is able to sense this, there might be indicators which can be measured and analyzed by an algorithm which then can make assumptions about the mood of a group of people.

In the intelligent building, we can identify three groups of variables which have influence on the well-being and the mood of users. First there is the *direct influence*. This category includes objectively measurable variables like temperature, lighting, air quality, noise or even olfactory influences. Related work showed that users have individual needs, which are not met by setting fixed values that define the climate of a room. By reacting to these needs it was shown that the satisfaction and the well-being of the users is improved and at the same time it is possible to reduce energy consumption and costs. Thus, acceptance of smart technologies can be increased. Individual variables in this group are already comparatively well covered by research. However, there is no comprehensive examination and the consideration of interactions regarding several variables or groups of people instead of individuals.

The second group of variables is the *indirect influence*, or well-being and complacency as being externally affected, with factors like time of the year/season, room size, the number of the people inside the room, the time of day but also floor plans or similar information. Typically, variables of this group affect users subconsciously and are difficult to influence or cannot be influenced at all. Nevertheless, they play an important role for well-being and complacency.

The third group is the *psychological* or *subjective factor*. Since people have different views, conceptions, wishes and needs, all of the previously mentioned influences have an individual effect. Even for the parameter temperature, when examined as an isolated variable, related work shows that there are different personal wishes and preferences for its value. Additionally, the basic emotional state of a person is an influencing factor.

This third group, therefore, plays an important role and enables a classification of data from the two previously mentioned because it is the only valid source of information about complacency and well-being of a person. For statements to be made, their data must be interrelated. Data for this third category can for example be obtained by questioning the users or gathering personal information using portable sensors or wearables. As the related work shows, data like differences in skin temperature, heart frequency or skin conductance can give significant information on the current mood of the user.

It is obvious that only the first group, the *direct influence*, can be controlled externally, in our case by the intelligent building. However, all groups of variables should be used to determine the degree of satisfaction of users. We assume that it is also possible to identify parameters that need to be adjusted in order to increase the well-being and complacency and by doing so reduce the reactance towards intelligent building technologies and ensure that building automation is able to achieve its objectives: improving the living and working environment of the inhabitants and reducing costs and energy consumption.

To realize this, we deem it important first to determine significant variables and the corresponding sensor technology to measure them in sufficient accuracy to collect data which in a next step allows to make correct and meaningful statements. It has to be ascertained whether the statements and results that have proven to work in scenarios with individual persons and limited parameters can be applied to groups of persons as well. It is to be assumed that the group characteristics differ from individual considerations. It is also necessary to examine the extent to which the three groups of variables influence each other and also to find possible dependencies within each group. Hence, we will set up a research and data collection program which will investigate this issue. On the basis of the present variables, it can be assumed that a clustering problem is given here and that it can be solved with methods and algorithms of machine learning.

There are two possible approaches. On the one hand, the unlabeled data can be used as an unsupervised learning task. On the other hand, the information from the third group, the data generated by the user himself, can be used to label direct influence and indirect influence data. Thus, approaches of semi-supervised learning are also possible. We plan to follow along both paths to evaluate the success rate in both cases. A big advantage of the second approach is that - once a model which generates reliable statements is established - this data source is not needed anymore. Personal information is always sensitive with respect to privacy and security and portable sensors and wearables can restrict users or cause discomfort. This is why an important goal is also to minimize inferences for the users. A model can also be used to make predictions. This is especially important in the context of buildings since they form an inert system and it takes time to react to new situations.

We plan to do further research on parameters and variables which are related to well-being in buildings. The related work showed that some areas are better covered than others. Thus, preliminary tests may be needed for variables which require further research. Once the variables are defined, sample data in real world scenarios can be gathered. For this we will work with an accordingly equipped functional building which also acts as a living lab. The data will be preprocessed to get a better understanding of the sample data. At this point, the results from questioning the users can be used to label data, at least to a certain extend. Machine learning algorithms (e.g. k-means, mixture models, hierarchical clustering) can then be used for the following tasks:

1. Determination of the statements which should be identified by the combination of the data, or in other words definition of goals for the algorithms.
2. Selection and testing of promising algorithm candidates from the fields of unsupervised and semi-supervised learning.
3. Further development and adaptation, as well as tuning of the algorithms by evaluation and optimization.
4. Validation of results with information on well-being from user interviews.

4 Architecture

Based on the explanations in chapter 3, we have developed an architecture (figure 3) to analyze inhabitant well-being. For this purpose, the data from the groups of direct influences (shown in yellow), subjective influences (shown in red) and indirect influences are analyzed first. The sensor data are mostly interpreted as time series, since our first preliminary tests in feature engineering have shown that the consideration of temporal dependence offers a higher information density and therefore more accurate classification potential. Based on the data, a personal model of each user is created. This already allows statements to be made about the well-being of separate individuals.

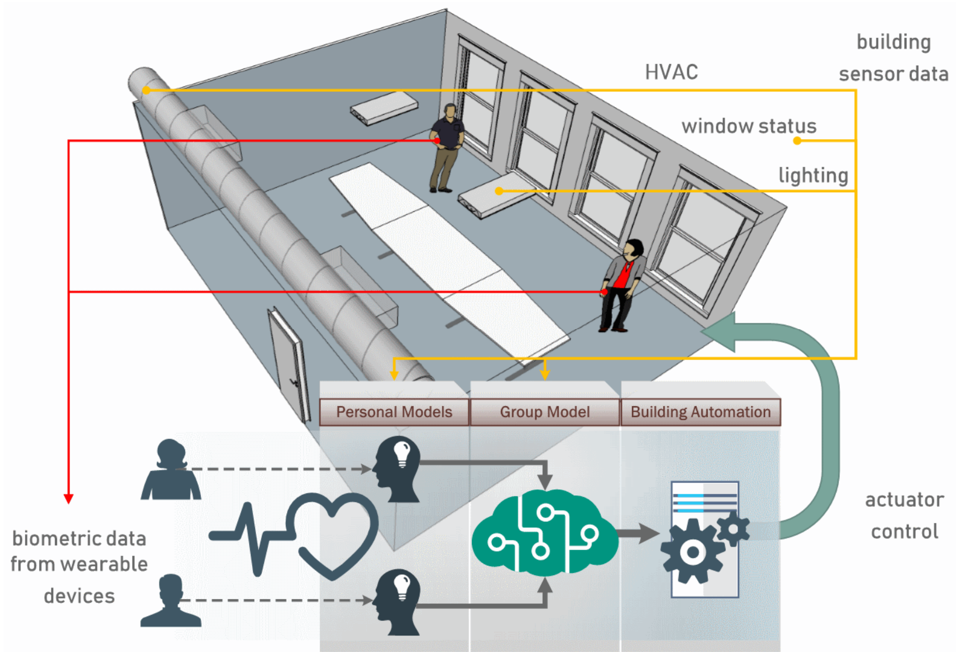

Fig. 3: Architecture

In a second step, the personal model is also used as input to create a group model. Again, data from direct and indirect influences are used to generate features. By combining the statements from the models of the first step, gathering information about the status of the group is possible. The group model now contains information about the current state of the room and the well-being of the users and thus also about possible grievances of the variables. Based on this information, building automation can now make changes if necessary, which are likely to improve the situation. The evaluation of this assumption shall be a major research target.

In a preliminary test, sample data of an intelligent building was used to create a set of promising feature transformation functions. Using these features, simple queries were formulated at first. Trying to detect weekends or occupancy purely based on the variables temperature and CO_2 yielded very promising results with a success rate of up to 100%. This shows the viability of the approach.

5 Conclusion

This paper reviews the current state of science and technology on the detection and recognition of complacency and well-being of individuals and groups of people in intelligent buildings. We showed that most of the current research projects refer merely to partial areas of this problem and concluded that there is a need of further research. However, the results are often encouraging, suggesting that recognition of general well-being could in principle be possible. Unlike a large part of the related work, we propose a comprehensive consideration of all variables to detect complacency and the well-being of users in order to enable smart buildings to react to the needs of the inhabitants and users accordingly.

Our goals are to establish a correlation between sensor data and subjectively felt well-being and to identify well-being or discomfort in groups of people. For this we want to create and utilize a broad dataset which contains all variables related to well-being. The resulting clustering problem can be solved by using methods and algorithms of unsupervised learning. An architecture for a system that meets the requirements as well as first promising preliminary tests were presented.

We address this problem because smart building technologies become more important and start to be a lot more common in everyday life.

6 Future Work

After proving that it is possible to measure and detect complacency, the next step would be to use this information and enable smart buildings to react to the current needs of the inhabitants and users accordingly. For this it might be useful to first create a simulator to test different common scenarios but also special ones in order to examine the robustness of the system. The simulator can thereby help to further improve and optimize the machine learning algorithms used.

Subsequently, a prototype could be developed and be used to evaluate the system in a real case scenario. For this we can work with a smart building on campus which is built and equipped as a living lab and hosts offices, seminar rooms, labs, a canteen, a library and recreational rooms.

Bibliography

[Ba15] Bachmann, Anja; Klebsattel, Christoph; Budde, Matthias; Riedel, Till; Beigl, Michael; Reichert, Markus; Santangelo, Philip; Ebner-Priemer, Ulrich: How to use smartphones for less obtrusive ambulatory mood assessment and mood recognition. In (Mase, Kenji; Langheinrich, Marc; Gatica-Perez, Daniel; Gellersen, Hans; Choudhury, Tanzeem; Yatani, Koji, eds): the 2015 ACM International Joint Conference. pp. 693–702.

[Bi12] Bigalke, Uwe, ed. Der dena-Gebaeudereport 2012: Statistiken und Analysen zur Energieeffizienz im Gebaeudebestand. Zukunft Haus, Energie sparen - Wert gewinnen.Berlin, 2012.

[Br72] Brehm, Jack: Responses to loss of freedom: A theory of psychological reaktance. General Learning Press, Morristown, 1972.

[CHPH14] Carreras, J.; Higuera, J.; Perálvarez, M.; Hertog, W.: Hybrid smart lighting and climate control system for buildings. In: IET Conference on Future Intelligent Cities. 4-5 Dec.2014.

[CL12] Choi, Joon-Ho; Loftness, Vivian: Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations. Building and Environment, 58:258–269, 2012.

[De13] Dettmann, André; Jentsch, Martin; Leiber, Paul; Bullinger, Angelika C; Langer, Dorothea: User in the loop: Konzeption und Entwicklung von Nutzerschnittstellen für"Mobilityon- demandKonzepte. In: Conference on Future Automotive Technology-Focus Electromobility. volume 18, pp. 03–19, 2013.

[Eh16] Ehrenbrink, Patrick; Hillmann, Stefan; Weiss, Benjamin; Möller, Sebastian: Psychological Reactance in HCI: A Method Towards Improving Acceptance of Devices and Services. In: Proceedings of the 28th Australian Conference on Computer-Human Interaction. OzCHI '16, ACM, New York, NY, USA, pp. 478–482, 2016.

[EP04] EPA, GB: Buildings and the Environment: A Statistical Summary Compiled by: US Environmental Protection Agency GB Workgroup. Environmental Protection Agency Green Building, Washington, DC. Available at: www. epa. gov/greenbuilding/pubs/gbstats. Pdf (accessed 2 October 2008), 2004.

[ESKB16] Exler, Anja; Schankin, Andrea; Klebsattel, Christoph; Beigl, Michael: A wearable system for mood assessment considering smartphone features and data from mobile ECGs. In (Lukowicz, Paul; Krüger, Antonio; Bulling, Andreas; Lim, Youn-Kyung; Patel, Shwetak N., eds): the 2016 ACM International Joint Conference. pp. 1153–1161.

[Fi16] Fiedler, Eckehard: DIN EN ISO 7730 in der Praxis. In: Proceedings of the TGAKONGRESS. Berlin, Germany, pp. 90–91, 2016. Towards the Empathic Building 13

[FGCL16] Frešer, Martin; Gradišek, Anton; Cvetković, Božidara; Luštrek, Mitja: An Intelligent System to Improve T-H-C Parameters at the Workplace. In: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct. UbiComp '16, ACM, New York, NY, USA, pp. 61–64, 2016.

[IO05] International Organization for Standardization: ISO 7730 2005-11-15 Ergonomics of the Thermal Environment: Analytical Determination and Interpretation of Thermal

Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria. International standards. ISO, 2005.

[He16] Heine, Thomas; Buhr, Daniel; Eschweiler, Gerhard; Weimar, Udo: Cross-generational Smart Environment Acceptance: Experiences of Experiencing Smart Environments at the LebensPhasenHaus. In: Proceedings of the 1st Workshop on Embodied Interaction with Smart Environments. EISE '16, ACM, New York, NY, USA, 2016.

[HR17] Harfield, Antony; Rattanongphisat, Waraporn: Towards an open monitoring platform for improving energy efficiency and thermal comfort in public buildings. In: 9th International Conference on Knowledge and Smart Technology (KST), 2017. pp. 150–155.

[Ki13] Kim, Yongsung; Eberle, Julien; Hanninen, Riikka; Un, Erol Can; Aberer, Karl: Mobile Observatory: An Exploratory Study of Mobile Air Quality Monitoring Application. In: Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication. UbiComp '13 Adjunct, ACM, New York, NY, USA, pp. 733–736, 2013.

[KP09] Kim, Sunyoung; Paulos, Eric: inAir: Measuring and Visualizing Indoor Air Quality. In: Proceedings of the 11th International Conference on Ubiquitous Computing. UbiComp '09, ACM, New York, NY, USA, pp. 81–84, 2009.

[LB99] Leaman, Adrian; Bordass, Bill: Productivity in buildings: The 'killer' variables. Building Research & Information, 27(1):4–19, 1999.

[LLLZ13] LiKamWa, Robert; Liu, Yunxin; Lane, Nicholas D.; Zhong, Lin: MoodScope. In (Chu, Hao-Hua; Huang, Polly; Choudhury, Romit Roy; Zhao, Feng, eds): Proceeding of the 11th annual international conference on Mobile systems, applications, and services. Taiwan 2013 p. 389.

[MFS14] Min, Kyeong T.; Forys, Andrzej; Schmid, Thomas: Demonstration Abstract: Airfeed: Indoor Real Time Interactive Air Quality Monitoring System. In: Proceedings of the 13th International Symposium on Information Processing in Sensor Networks. IPSN '14, IEEE Press, Piscataway, NJ, USA, pp. 325–326, 2014.

[NEL15] Niforatos, Evangelos; Elhart, Ivan; Langheinrich, Marc: Public displays for monitoring and improving community wellbeing. In (Mase, Kenji; Langheinrich, Marc; Gatica-Perez, Daniel; Gellersen, Hans; Choudhury, Tanzeem; Yatani, Koji, eds): the 2015 ACM International Joint Conference. pp. 775–778.

[RUU10a] Raab, Gerhard; Unger, Alexander; Unger, Fritz: Die Theorie psychologischer Reaktanz. In (Raab, Gerhard; Unger, Alexander; Unger, Fritz, eds): Marktpsychologie, pp. 65–76. Gabler, Wiesbaden, 2010.

[RUU10b] Raab, Gerhard; Unger, Alexander; Unger, Fritz, eds. Marktpsychologie. Gabler, Wiesbaden, 2010.

[SSCS16] Snow, Stephen; Soska, Anna; Chatterjee, Shre Kumar; schraefel, m.c.: Keep Calm and Carry On: Exploring the Social Determinants of Indoor Environment Quality. In: Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems. CHI EA '16, ACM, New York, NY, USA, pp. 1476–1482, 2016.

[WAL79] Wyon, D. P.; Andersen, I.; Lundqvist, G. R.: The effects of moderate heat stress on mental performance. Scandinavian journal of work, environment & health, 5(4):352–361, 1979.

[WHHB15] Wilson, Charlie; Hargreaves, Tom; Hauxwell-Baldwin, Richard: Smart homes and their users: a systematic analysis and key challenges. Personal and Ubiquitous Computing, 19(2):463–476, 2015.

[ZLW14] Zhang, Liang; Lam, Abraham Hang-yat; Wang, Dan: Strategy-proof Thermal Comfort Voting in Buildings. In: Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings. BuildSys '14, ACM, New York, NY, USA, pp. 160–163, 2014.