CISBAT 2019 International Conference - Future Buildings & Districts - Energy Efficiency from Nano to Urban Scale, Lausanne, Switzerland

Is your clock-face cozie? A methodology for the in-situ collection of occupant comfort data

P. Jayathissa[a,*], M. Quintana[a], T. Sood[a], N. Narzarian[b], C. Miller [a,]

[a]*Building and Urban Data Science Group, Department of Building, Singapore*
[b]*University of New South Wales, Australia*

Abstract

Keywords: Comfort Feedback, Data Collection, Fitbit, Comfort Recommendation, Mood Logging

1. Introduction

In the Maōri legends of old, there was a time when the sun would travel quickly across the sky, leaving people without sufficient light and warmth. Māui, a great hero of the time, observed this discomfort amongst the village and went on a quest to tame the sun. Armed with his magic jawbone of Murirangawhenua and a lot of flax rope, he succeeded in tying down the sun and beating it, until it slowed down to the speeds we have today. What Māui effectively did was categorise everyone in a one-size-fits-all model, and based on this assumption, took action to change the environment he lived in.

The way we control our buildings today, is similar to the way that Māui tamed the sun. We make an assumption of the general population based on a survey of a few people, and change the environment we live in based on these few data points. The issue here is that we assume that all occupants within a building zone share the same comfort preferences. In reality, variations in metabolic rates, light preferences, and noise tolerances presents a challenge when attempting to condition a work space to meet the requirements of all occupants.

However understanding the preferences of individuals presents a significant challenge, both the times of Māui and now. The state of the art of human comfort data collection is in the form of surveys, either as an online form, or paper based. While this in principal works, it presents three major challenges.

- The methodology cannot be scaled to large sample sets due to the administrative overhead in preparing these studies.

*Corresponding author
Email addresses: `p.jayathissaa@nus.edu.sg` (P. Jayathissa), `matias@u.nus.edu` (M. Quintana), `matias@u.nus.edu` (T. Sood), `n.nazarian@unsw.edu.au` (N. Narzarian), `clayton@nus.edu.sg` (C. Miller)

- The studies are often conducted outside of the test subjects natural working environment.
- Users suffer from survey fatigue [1] due to the number of data points required to conduct a thorough assessment. Even when willing to participate, there is a concern about how accurately their responses are [2].

This paper presents cozie, a publicly available clock-face designed for fitbit which can be used for tailored, scalable, in-situ human comfort studies. We will show how the watch-face can be deployed for a range of tailored experimental scenarios, and be evaluated using modern data analytics to infer behavioral patterns of the test participants. This information can be used to optimise human comfort through spatial recommendation, or combined with building sensor data to create a labeled data-set for the comfort optimisation of the building management system.

The remainder of the paper is organised as follows. The next section outlines the cozie clock-face and how research teams can implement it for a variety of human comfort related experiments. In Section 3 we detail a preliminary experiment conducted using the cozie clock-face for building comfort optimisation, Section 4 presents the preliminary results from this experiment, and Section 5 discusses our findings and next steps in this project. Finally, Section 6 concludes the paper.

2. The cozie watch-face

Cozie is built as a clock-face for fitbit, a wearable health tracker with 25 million active users [3]. The application is publicly available for download at the following link [insert link]

2.1. Overview

In this section we define "user" as the test participant who is wearing the fitbit, and "manager" as the person coordinating the experiment.

The default status of the clock-face is a simple binary question: "Comfy" or "Not Comfy", as seen in Figure 1. By simply clicking one of the icons, information about the users location (GPS), heart-rate, steps walked since last log, and the comfort data is anonymously sent to an Influx time series cloud database [Ref influx]. Data from this database can be simply queried with an API key that can be provided to the manager. Further documentation can be found on the cozie website [insert link].

If the manager is interested as to why the user is feeling discomfort, then there is a range of additional questions that can be configured using the cellphone that the fitbit is paired with. The optional questions include: thermal preference, light preference, noise preference, indoor/outdoor, mood, and whether the user is in office. These settings, along with a unique user-id for each user, and a unique experiment-id can be configured by the manager using the cellphone that the fitbit is paired with. The watch-face also has the ability to prompt the user and force them to provde feedback at custom intervals set by the manager.

3. Example Experimental Methodology

An experient was conducted at co-working spaces at the National Unviersity of Singapore. 15 participants were recruited for the experiment and equiped with a fitbit watch. The watch settings

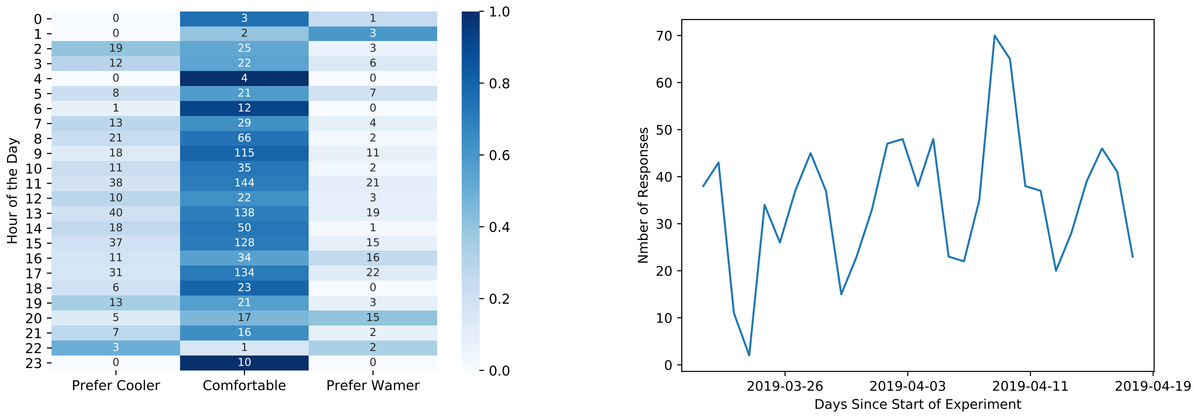
Figure 1: Using the fitbit mobile application to design a survey flow

Figure 2: Strap-Pack

were set to also request thermal preference (prefer warmer, prefer cooler, comfy), and the set to force request feedback at the hours of 9:00, 11:00, 13:00, 15:00, and 17:00

The watch was further complimented with IoT connected on-body and environmental sensors shown in Figure 2. The onbody sensor consists of a temperature and light sensor from mbient-labs that had been modified to fit the watch strap with a custom 3d printed case. An off body sensor measuring temperature and humidity was attached to the participants bag. The sensors communicate via bluetooth to raspberryPi gateways that had been positioned throughout the working space.

Data from the cozie watch face, and the environmental sensors were aggrigated in an Influx cloud time-series database, which served as a platform for data aquisition and fault detection. Simple algorithms written in python can dynamically pull the data from the Inlfux servers and process them for a variety of needs that will be expaned in the next section. Source codes can be found here [ref aurek-data-crunch repo].



(a) (b)

Figure 3: (a) Aggregation of user feedback mapped to the hour of the day that feedback was given. Annotations within the heat-map detail the absolute response value, while the colour gradient relates to the normalised values (b) Daily responses during the course of the evaluation period. The dips in the graph are weekends

4. Results

The experiment consisting of 15 users each equipped with a fitbit over a month, produced a dataset of [INSERT NUMBER HERE] data points. Each data point is effectively a survey of the user at a particular time. The results presented in this section is a demonstration of the type of analysis that can be conducted using data acquired from the cozie watch-face.

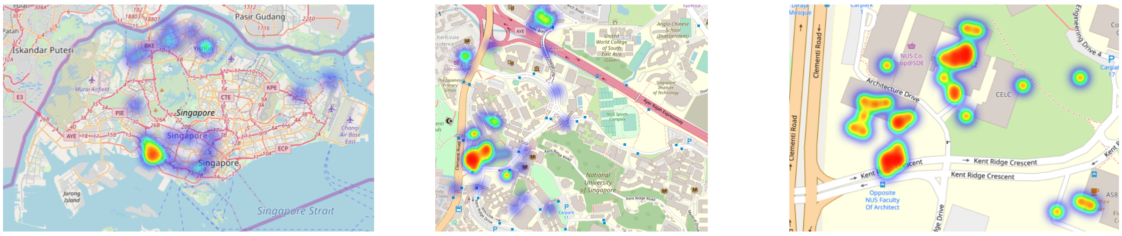
4.1. Evaluational of user comfort over a day

Figure 3a details a simple heat-map where the user comfort feedback is mapped to the hour of the day. Users appear to be comfortable on average [INSERT NUMEBR HERE] % of the time, and there are no statistically significant trends during working hours (9:00 - 17:00). Variations in user comfort feedback during the day can be used to infer an issue within the building.

It is interesting to note that there is on average [INSERT NUMBER HERE] times more responses in the hours of 9:00, 11:00, 13:00, 15:00, and 17:00 which is when the occupant is buzzed and asked to give feedback. Nevertheless there are still significant amounts of responses made outside these times which had been done from the motivation of the participants themselves. Figure 3b details the daily responses from the participants, and no observable decrease in responses can be made. Dips in responses naturally occur during the weekend.

4.2. Influence of Individual Users

Individual user feedback can be clustered using un-supervised learning techniques. In this example, we use a hierarchal k-means clustering based on euclidean distance using the Nearest-Point-Algorithm. The results, shown in Figure 5a, show four distinct clusters of users. Understanding and defining these differences in user preferences can be used to recommend spaces that may better suit the needs of the occupant. For example, User 5 and User 10 can be recommended working



(a) City of Singapore (b) National University of Singapore (c) School of Design and Environment

Figure 4: Map of responses. The experiment was conducted at co-working spaces at the school of design and environment, however responses are seen throughout Singapore. Note that these results only show 172 of the [INSERT NUMBER] total responses as GPS localisation often failed indoors.

spaces that are on average cooler. User 13 on the other hand appears to have a broad comfort spectrum.

It is important to note here that the data is not entirely representative of a single building space, as the user may have given feedback while having lunch outside. There are even feedback results made outside of working hours as seen in 3a 3b. Conclusions such as "Building Zone A was comfortable 80% of the time" can therefore not be made. This will be further discussed in Section 5.

4.3. Influence of Heart-Rate

It is widely known that heart-rate influences metabolic activity, and therefore an occupants comfort preference. Figure 6a details the number of responses for each thermal response based on the heart rate. [INSERT NUMBER HERE] % of "Prefer Cooler" responses occurred during higher metabolic activity when the heart rate was greater than 100 beats per minute. If we filter out these responses,and apply the same algorithms detailed in Section 4.2, we see a slightly different response and clustering pattern, as shown in Figure 5b.

4.4. Combination with Sensor Data

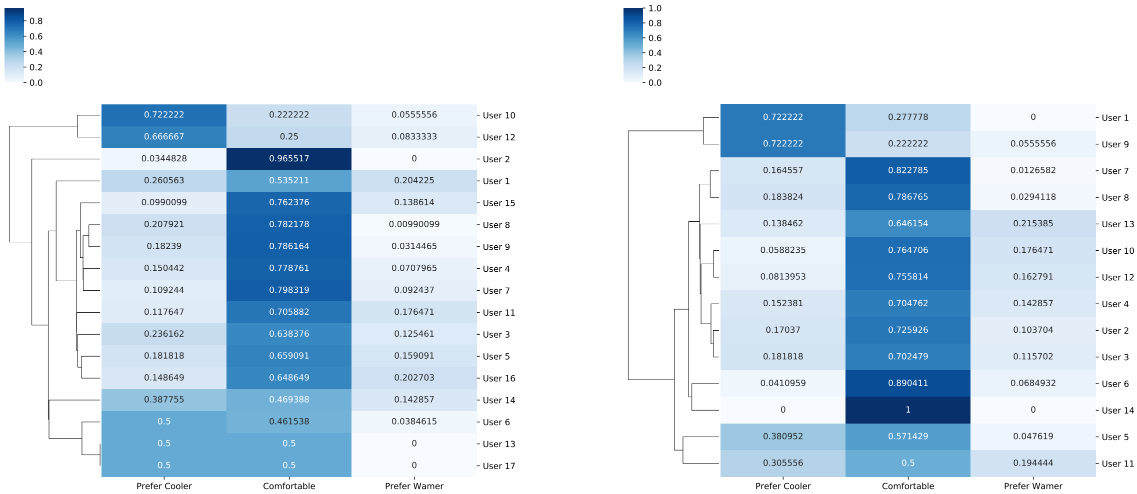
Combining the cozie watch face, with the "strap-pack", an environmental sensor addition to the watch face opens another dimension of analysis. User responses are mapped to the environmental condition at which they are exposed to, which can provide a high quality labeled data set for training data driven models.

[FOR MATIAS TO FILL OUT]

5. Discussion

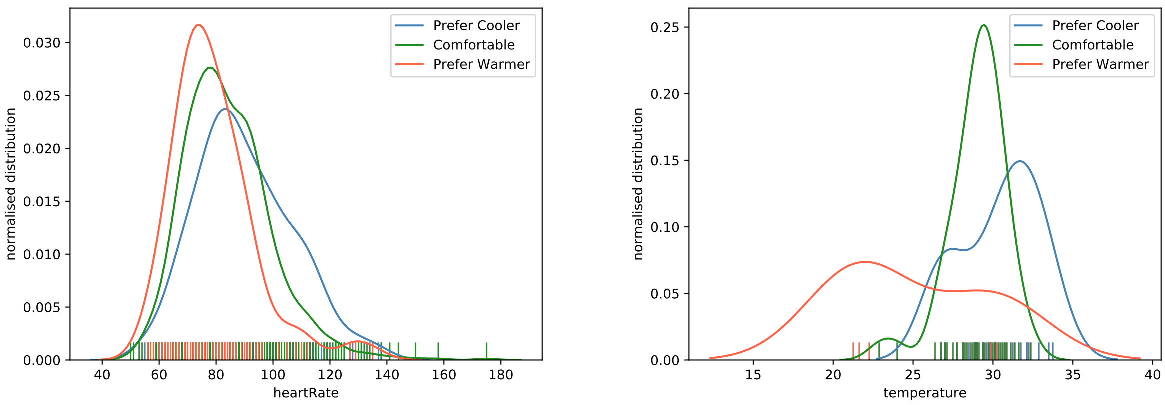
5.1. Large Uncontrolled Data vs. Small Controlled Data

Let us take a step back and observe how market analysis was conducted. Traditionally, super markets would call individual households and ask for their feedback about what products they would like to have in stock. In modern times, applications such as facebook mine preference data from users based on what posts they "liked", and use this to generate targeted advertising for each individual.



(a) (b)

Figure 5: Clustering of user feedback using hierarchal k-means. (a) The full results show four distinct clusters, (b) filter by heart rate that is less than 100 beats per minute



(a) (b)

Figure 6: Normalised distribution of the response type based on (a) heart rate (b) temperature. Note that the data sets for the temperature only contains 79 of [insert total number of data] data points due to data losses in the wearable sensors

One can draw these parallels to human comfort surveying. Placing a group of participants in a controlled experimental space and conducting feedback surveys is a trusted traditional method for human comfort surveys. Giving each participant a smart watch, and analysing the patterns of hundreds of data points per user would be more akin to modern data analytics employed in industries outside the building sector.

While they both work, the types of conclusions that can be derived are different. The traditional method can derive conclusions such as "4 of the 20 users felt warm at temperatures higher than 25.6 °C". Whereas the uncontrolled, large data method can draw conclusions such as "4 of 20 users can be catergorised as a user type that prefers cooler working environments".

To further add to this, the uncontrolled method has minimal management overhead, and can be scaled by purchasing more devices, thus providing an even richer data set along the user axis.

5.2. In-situ benefits and limitations

The cozie watch face enables users to be analysed in-situ. By this we mean that the users work in their natural work environment, and give feedback with minimal effort. As introduced in Section 1 this allows the experiments to be conducted and scaled with minimal management overhead; the users don't feel like they are in an experimental setting as they are in their normal office; and finally there is no observable survey fatigue. As described in Figure 3b there is no observable decrease in the feedback given. In fact, some of the users have enjoyed owning a fitbit, and will keep the device provided that they keep the cozie clock-face.

The limitation however is the control of the users. Users work from their designated co-working space at their own will, and at their own time. They may decide to work from home, or are at lunch in an outdoor restaurant when giving feedback. This presents a limitation in the context of traditional small controlled datasets. With larger samples however, this uncontrolled situation presents an opportunity to better understand the behavioral characteristics of a user as certain patterns can be derived and interpreted. If the research manager would like to have more control of the experiment they may choose to also add the "In Office / Out of Office" or the "Indoor/Outdoor" question to the list of questions asked.

5.3. Indoor Localisation

The clock-face collects GPS data from the fitbit, however GPS data indoors is not always reliable, and often is not accessible. Other indoor localisation techniques such as pattern matching of noise data to indoor sensors [CITE JUN] are proven methods that may improve the results. Alternatively, the research institution may consider investing in indoor localisation technologies such as Steerpath which has recently been installed in buildings at the School of Design and Environment.

5.4. Problems Encountered

During the course of the experiment two fitbits were lost by the users. One was lost permanently, and the other was found at a later date. There were also some issues with the collection of the enviornmental sensor data, resulting in only [Insert number here] matching points of the comfort feedback to the sensors, where as we expected at least 400 matching points.

6. Conclusion

First trial runs of the cozie application for occupant comfort data collection have prooven successful. Within just four weeks [INSERT NUMBER] data points of thermal comfort were obtained from the 20 test participants, with minimal administrative overhead. This rich data set provides new opportunities in analysing occupant comfort behaviour through data driven methods. Within this paper, we have demonstrated how the data can be manipulated and clustered to group people into various comfort profiles. In our case there were [INSERT NUMEBR HERE] distinct groups, which can be then recommeneded spaces that better suit their comfort profile. The data can also be clustered via time to display building defects, or annomylies in occupant behaviour. Finally, we demonstrate how the app can be combined with wearable environmental sensors to cross reference a users preference to the environment that they were in.

The watch-face is publically available for download at this link, and we strongly encourage the readers to contact the authors if they have any questions or recommendations.

Next steps in this research involve using cozie for the exploration of occupant clustering and spatial recommendation. We will explore elements of sound, light, and thermal comfort to determine whether spatial recommendation can serve as an alternative to individualised adaptive buildings control. Furthermore, the developement of a ”strap-pack”, a smart-watch environmental sensor that can be adapted to the watch strap is underway.

References

[1] S. R. Porter, M. E. Whitcomb, W. H. Weitzer, Multiple surveys of students and survey fatigue, New Directions for Institutional Research 2004 (121) (2004) 63–73.

[2] A. K. Clear, S. Mitchell Finnigan, P. Olivier, R. Comber, ThermoKiosk: Investigating Roles for Digital Surveys of Thermal Experience in Workplace Comfort Management, Proc. of CHI (2018) 1–12doi:10.1145/3173574.3173956.

[3] Fitbit 2018 investor report (2018).
URL `https://investor.fitbit.com`