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

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Abstract. Labelled human comfort data can be a valuable resource in optimising the built environment, and improving the wellbeing of individual occupants. The acquisition of labelled data however remains a challenge. This paper presents a methodology for the collection of in-situ occupant feedback data using a Fitbit smartwatch. The clock-face application *cozie* can be downloaded free-of-charge on the Fitbit store and tailored to fit a range of occupant comfort related experiments. In the initial trial of the app, fifteen users were given a smartwatch for one month and were prompted to give feedback on their thermal preferences. In one month, with minimal administrative overhead, 1460 labelled responses were collected. This paper demonstrates how these large data sets of human feedback can be analysed to reveal a range of results from building anomalies, occupant behaviour, occupant personality clustering, and general feedback related to the building. The paper also discusses limitations in the approach and the next phase of design of the platform.

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 and went on a quest to tame the sun. Armed with his magic jawbone of Murirangawhenua, he tied down the sun and beat it, until it slowed down to the speeds we have today. What Māui did was categorise everyone in a one-size-fits-all thermal comfort 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 method that Māui used. 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. From these methodologies, traditional thermal comfort research has produced comfort models based on indices such as the predicted mean vote (PMV). A recent review of data from dozens of such studies has shown that PMV is accurate only 34% of the time [1]. The issue with these models when applied in building practice, is the assumption that all occupants within a building zone share the same comfort preferences. In reality, variations in metabolic rates and the preferences or tolerances of each person presents a challenge when conditioning a workspace to meet the requirements of all occupants [2].

Understanding the preferences of individuals presents a significant challenge, both in the times of Māui and now. The state of the art uses wearable sensors that collect physiological parameters which can feed into human comfort models [3]. These sensors can be further complemented with

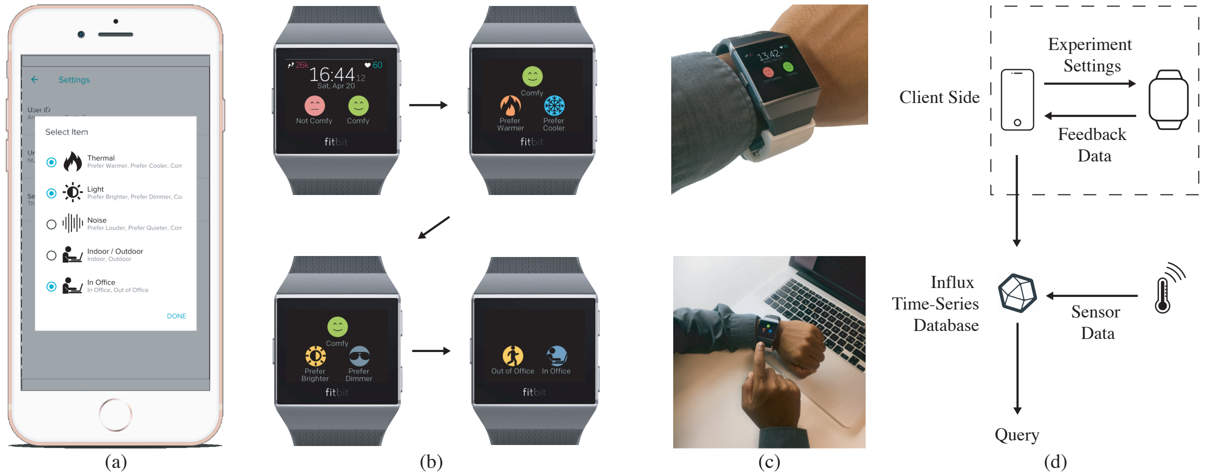

Figure 1: Overview of the cozie app platform: (a) the Fitbit mobile app is used to set experimental settings, (b) the flow of questions based on settings selected in (a), (c) photos of the watch-face using a Fitbit ionic, with the strap-pack sensor box, (d) overview of data communication.

the use of smartphone applications [4], or in the form of online or paper-based surveys. While these methods work, they have inherent difficulties:

- The methodologies often cannot be scaled to large sample sets due to the administrative overhead in preparing these studies.
- The studies are often conducted outside of the test subjects natural working environment, or uses devices that the user would not traditionally wear in their day to day life.
- Users suffer from survey fatigue [5] and even when willing to participate, there is a concern about how accurate their responses are [6].

We hypothesise that the use of a smartwatch clock-face to collect subjective comfort feedback, is a more scalable, and non-intrusive method, which also minimises survey fatigue due to the minimal effort required from users.

This paper presents *cozie*, a publicly available clock-face designed for the Fitbit smartwatch which can be used for in-situ human comfort studies. We will show how the clock-face can be deployed for a range of tailored experimental scenarios, and be evaluated using modern data analytics to infer behavioural 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 labelled data-set for the comfort optimisation of the building management system.

2. The cozie clock-face

Cozie is built as a clock-face for Fitbit, a smartwatch with 25 million active users. The application is publicly available for download from the cozie website[1]. In this paper, 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),

[1] `https://cozie.app/`

heart-rate, steps walked since the last log, and the comfort data is anonymously sent to an Influx time series cloud database [2]. Data from this database can be queried with an API key that can be provided to the manager.

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. The watch-face can also prompt the user with a gentle vibration and force them to provide feedback by hiding the clock until feedback has been given.

3. Experimental methodology

An experiment was deployed as part of *Project Coolbit*[3], an international effort that focusses on the use of smartwatches for human comfort analysis [7]. Fifteen participants residing in Singapore were recruited for the experiment and were equipped with Fitbit Versa or Ionic watches. Most of the participants were working at the National University of Singapore (NUS) at several flexible workspaces around campus. The *cozie* clock-face was set to request thermal preference (prefer warmer, prefer cooler, comfy), and the set to request feedback at the hours of 9:00, 11:00, 13:00, 15:00, and 17:00.

The watch was further complemented with Internet-of-Things (IoT) connected on-body and environmental sensors. The on-body sensor consists of a temperature and light sensor from *mbient-labs*[4] 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 participant's bag. The sensors communicate via Bluetooth to Raspberry-Pi gateways that had been positioned throughout the working space. Data from the cozie clock-face and the environmental sensors were aggregated in an Influx cloud time-series database, which served as a platform for data acquisition and fault detection.

4. Results

The experiment, consisting of fifteen users each equipped with a Fitbit over a month, produced a data set of 1,460 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* clock-face.

4.1. Overview of spatio-temporal data

Figure 2a details the spatial distribution of data throughout Singapore. Each of these data points is tagged with the users heart-rate, response, and local temperature which can be used to infer faults or issues within the building. Figure 2b is a simple heat map plotting the number of responses based on the hour of the day, and day of the week. It is interesting to note that 55% of responses come from the hours of 9:00, 11:00, 13:00, 15:00, and 17:00 when the occupant is buzzed and forced to give feedback. The remaining 45% of responses are made outside these times through the self-motivation of the participants themselves. Figure 2c details the daily responses from the participants, and no observable decrease in responses can be made, indicating no effects of survey fatigue. Dips in responses naturally occur during the weekend, and during the first week when users were still being onboarded. A normal distribution of heart-rate data from the Fitbit heart rate sensor can be found in Figure 2d.

[2] https://github.com/influxdata/influxdb

[3] http://www.projectcoolbit.com

[4] https://mbientlab.com/

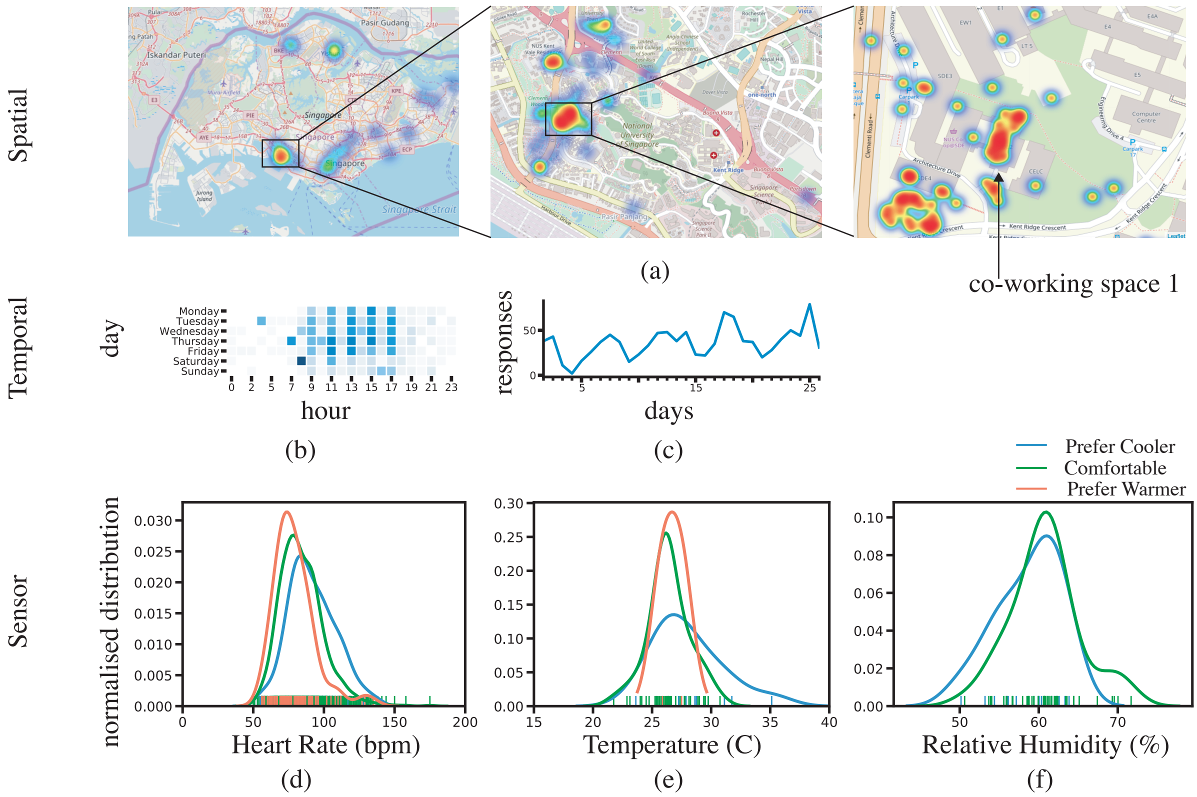

Figure 2: Overview of raw data extracted from the cozie clock-face and additional sensors. (a) spatial distribution of responses throughout Singapore, (b) temporal distribution of responses, (c) number of responses per day over the course of the experiment, (d-f) rug plots detailing the normalised distribution of responses based on the Fitbit heart rate sensor, wrist-mounted temperature sensor, and off-body humidity sensor

4.2. Merging with environmental sensor data

Combining the cozie clock-face, with additional environmental sensors opens further dimensions of analysis. User responses are mapped to the environmental condition at which they are exposed, which can provide a high quality labelled data set for training data-driven models. Figure 2e-f detail the distribution of temperature and humidity data. Unfortunately, due to communication issues from these sensors, not all data points could be recorded. The temperature of the strap-mounted temperature sensor is on average 0.8 °C warmer than the surrounding environment due to the influence of body temperature.

4.3. Clustering of thermal comfort personality

Individual user feedback can be clustered using unsupervised learning techniques. In this example, we use a hierarchical k-means clustering based on Euclidean distance using the nearest-point-algorithm. The results, shown in Figure 3, 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, Group A, which primarily works off-site can be recommended alternative workspaces that are on average cooler. Group C on the other hand is a single highly satisfied user, who works from a single work-space within a narrow temperature range, and relatively low resting heart-rate. Group D represents our conventional occupant that may be comfortable 70% of the time.

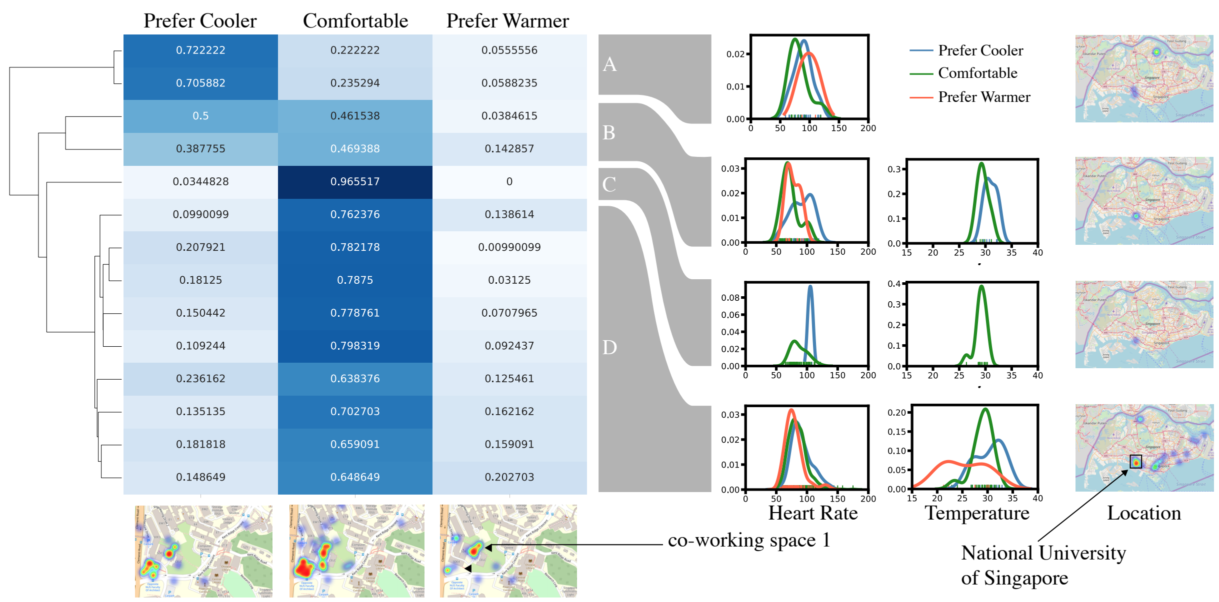

Figure 3: Hierarchical clustering heatmap of user feedback using k-means with Euclidean distance. The numbers within the cluster-map detail the normalised number of responses. Four distinct groups can be observed. (A) two users that generally prefer cooler environments to their norm, (B) users that are comfortable 50% of the time, (C) user that is almost always comfortable, (D) users that are comfortable on average 70% of the time. To the right are breakdowns of the respective groups via sensor data and location. Below the cluster plot are spatial distributions of feedback responses at the university.

Below the cluster plot are spatial distributions of responses that can be used to identify different building climates. The majority of *Prefer Warmer* responses occur in co-working space 1. This area can be labelled as a *cooler working space* for users that would prefer cooler working environments. Alternatively, if facilities management wishes to save energy, increasing the set-point temperature of these *over-cooled* spaces may be a low effort solution which may simultaneously improve occupant well-being.

5. Discussion

5.1. Large uncontrolled data vs. small controlled data

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 smartwatch, 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. Both methods are useful for reaching different types of conclusions. The traditional method can derive conclusions such as: *4 of the 15 users felt warm at temperatures higher than 25.6 °C*. This insight is useful in the context of the previously mentioned generalizable thermal comfort models that are traditionally created in built environment research, but have poor accuracy. On the other hand, the uncontrolled, large data method can draw conclusions such as: *4 of 15 users can be categorized as a user type that prefers cooler working environments*. This paper focuses on the use of clustering to show the groups of *comfort personality types*.

5.2. In-situ benefits and limitations

Uncontrolled experiments have minimal management overhead, which means that it can be easily scaled to larger groups by purchasing more devices. Furthermore, the users are analysed in their natural work environments and give feedback with a simple click on their watch. This reduction of effort results in no fatigue in the number of voluntary responses given as shown in Figure 2c. While users generally work from their office, they sometimes work from home, or at a local cafe. This presents a limitation in the context of traditional small controlled data. Large enough data must be obtained to filter out these scenarios and interpret meaningful results.

5.3. Indoor Localisation

The clock-face collects GPS data from the Fitbit, however GPS data indoors is not always reliable, and often not accessible. Only 30% of all data points were tagged with GPS data. The team is currently investigating other methods such as Bluetooth based localisation from Steerpath, and pattern matching of wearable sensor data to indoor sensors.

6. Conclusion

First trial runs of the cozie application for occupant comfort data collection have proven successful. Within just four weeks 1460 data points of thermal comfort were obtained from the 15 test participants, with minimal administrative overhead. This rich data set provides new opportunities in analysing occupant comfort behaviour through data-driven methods. We have demonstrated how the data can be manipulated and clustered to group people into various comfort profiles. In our case, there were 4 distinct groups, which can be recommended spaces that better suit their comfort profile. The data can also be clustered via time to display building defects or anomalies in occupant behaviour. Finally, we demonstrate how the app can be combined with wearable environmental sensors to cross-reference a users preference to their environment. The open data repository for this paper can be found on Github[5].

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 development of a *strap-pack*, a smartwatch environmental sensor that can be adapted to the watch strap is underway.

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[5] `https://github.com/buds-lab/cisbat-cozie-paper`