Crowdsourcing occupant comfort feedback at a net-zero energy building in the tropics

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Abstract.

This study describes a human-building interaction framework called the *SDE Learning Trail*, a mobile app that is currently deployed at the SDE4 building - the new Net Zero Energy Building (NZEB) at the National University of Singapore (NUS). This framework enables building occupants and visitors to learn about the *well and green* features of the new NZEB while facilitating collection of environmental comfort feedback in a simple and intuitive way. Within just three months, 1163 feedback responses of thermal, visual and aural comfort were obtained. A total of 616 participants have contributed to the study till date, with 79 participants who provided five or more instances of feedback. This data set provides new opportunities for understanding occupant comfort behavior through supervised and unsupervised data-driven methods. This paper demonstrates how occupants can be clustered into comfort *personality* types that could be used as a foundation for prediction and recommendation systems that use real-time occupant behavior instead of rigid comfort models. We provide an overview of the application methodology and initial results in the SDE4 building.

1. Introduction

The concept of *Wellness* is becoming a major topic in research and industry. A focus of wellness is that the ability to meet an occupant's preferences can have an impact their well-being and productivity in the built environment. This emphasis is coming at a time when much of the literature regarding human preference of indoor environmental quality is being challenged. An analysis of the traditional predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), the two most widely used comfort indices, showed that their accuracy is only 34% across dozens of comfort studies in the last few decades [1, 2]. It is becoming apparent that individual differences in comfort preference could explain variations in environmental perception between occupants exposed to the same conditions. What may suit one group of occupants, may be unacceptable for others. Even though its understood that differences in individual comfort preferences exist [3], their quantitative identification presents significant challenges for researchers and practitioners in field conditions.

One answer to this dilemma is to increase the frequency and volume of building occupant user feedback. The contemporary methods of feedback collection include structured surveys or interviews - on-line or off-line, in person or remote. Conventional approaches have a number

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of shortcomings [4]. One of the key drawbacks of these methods in the field is scalability. Its difficult to collect large sample data sets due to the administrative, financial and other operational overheads of conventional approaches. In addition, factors such as lack of knowledge (respondents do not know the answer to a question, but answer it anyway), lack of motivation (respondents may not process questions fully) and failures in communication (survey questions may be unclear or misunderstood) are often associated with increased risk of biases and respondent heuristics in survey responses [5].

This paper presents a unique framework for collection of human comfort feedback in smart built environments called the *Learning Trail.* The human-building interaction framework enables building visitors and occupants to provide environmental comfort feedback while learning more about a building. Currently, the framework is deployed in a new Net Zero Energy Building (NZEB) at the School of Design & Environment, National University of Singapore (NUS). This work demonstrates how the collected data from building's occupants and visitors can be used to understand personalized comfort profiles of users. Further this deployment provides the proof-of-concept for a spatial recommendation system that utilizes the collected data to match occupant comfort profiles to suitable spaces in real time.

2. Methodology

As shown in Figure 1, the SDE Learning Trail is a guided tour of building's six different building features - Net Zero Energy, Water, Hybrid Cooling, Wellness, Tropical Architecture, and Biophilic Design - as distinct *trails* for users. Each trail is composed of a number of physical *stations* - in the form of placards that include explanatory labels and text as well as a QR code. These stations are spatially placed such that they help break down and explain the interesting building features in more detail. The framework is realised as a mobile web application which connects each station (QR code) with information and interactive visualizations online. As users complete each trail by visiting different stations, the application collects comfort feedback for thermal, visual and aural variables while enabling users to learn and appreciate the design, construction, and sustainability innovations.

A total of 35 stations (6 trails) were spread across the 6 floors of the new NZEB. The placement of a trail in the building was based on where the building feature was most pronounced. For example, the water trail stations were placed right next to the storm water feature, bio-retention basins and the detention tank for the building. This helped instantly contextualize the digital content of trails and stations with their physical location in the building. Stations were placed in proximity of fixed sensors measuring seven attributes in real-time: temperature, humidity, noise, light, carbon-dioxide, volatile organic compounds and presence. The stations were distributed across outdoor and indoor spaces based on trail configuration, station content, and proximity to fixed sensors. The interactive mobile web application was launched on Jan 30th, 2019 at the opening ceremony of the new NZEB. Over the next three months, staff and students from the university, external governmental, industrial and academic delegations were organized into groups for taking guided tours of the building by the research team from SDE.

Each participant in the guided tours used the interactive mobile application to go through trails as shown in Figure 2. Users could scan stations with the help of an embedded QR code scanner in the application. The application was built such that each user was prompted to provide temperature, light and noise level feedback though a 3-point scale as shown in Figure2c. Each user was prompted five times out of all the stations they visited to provide feedback during the guided tour. A total of 616 users used the application over three months, with 79 users providing over at least five votes each, totalling 1163 environmental comfort feedback points. The data from the users and fixed sensors was aggregated using a cloud-based, time-series database - which served as a platform for data acquisition, storage and error detection. The combination of location based user comfort feedback and fixed environmental sensor data

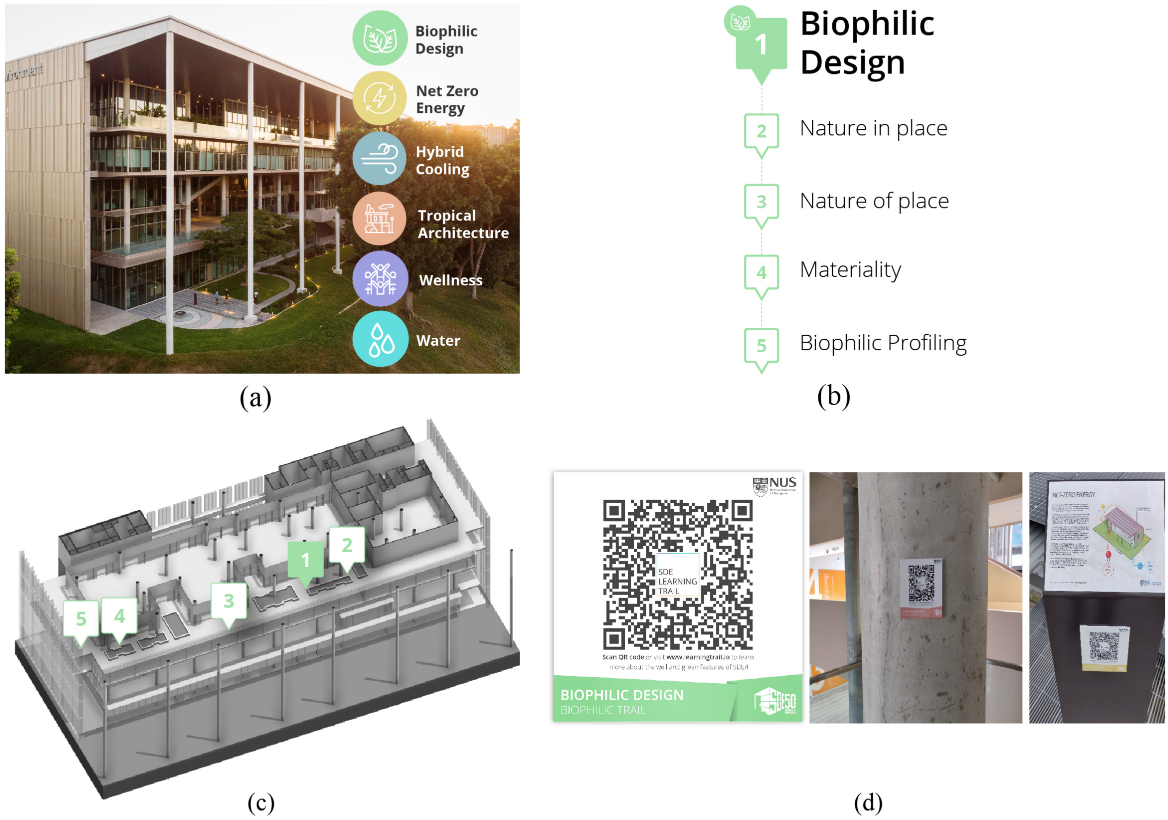

Figure 1: Overview of Experiment Setup: (a) Six building features described as trails, (b) Biophilic Design trail as an example of breaking down a trail into stations, (c) Biophilic Design trail as an example of trail placement in the building, (d) Digitisation of each physical station as a QR code.

allowed clustering analysis of personalized comfort profiles of users.

3. Results

For the purposes of this publication, only an initial analysis of the collected environmental quality preference data is provided. The emphasis is to apply an unsupervised clustering technique to the occupant data to segment the users who provide more than five feedback points into cohorts of similar behavior. This type of analysis is the foundation for further research studies that characterize comfort preferences in ways that are specific to each occupant, but generalizable by grouping similar preference behavior. This particular analysis focuses on the behavior of each user in their interaction with the system instead of the demographic, physiological, or environmental conditions variables that are typically addressed in environmental preference studies. The aspects will be evaluated in future research.

3.1. Discovering occupant personal comfort preferences

As shown in Figure 3, five distinct clusters can be observed based on differences in preferences for temperature, light and noise levels across users. Predominantly users were comfortable and seldom preferred a change to cooler or quieter environments. Its interesting to discover

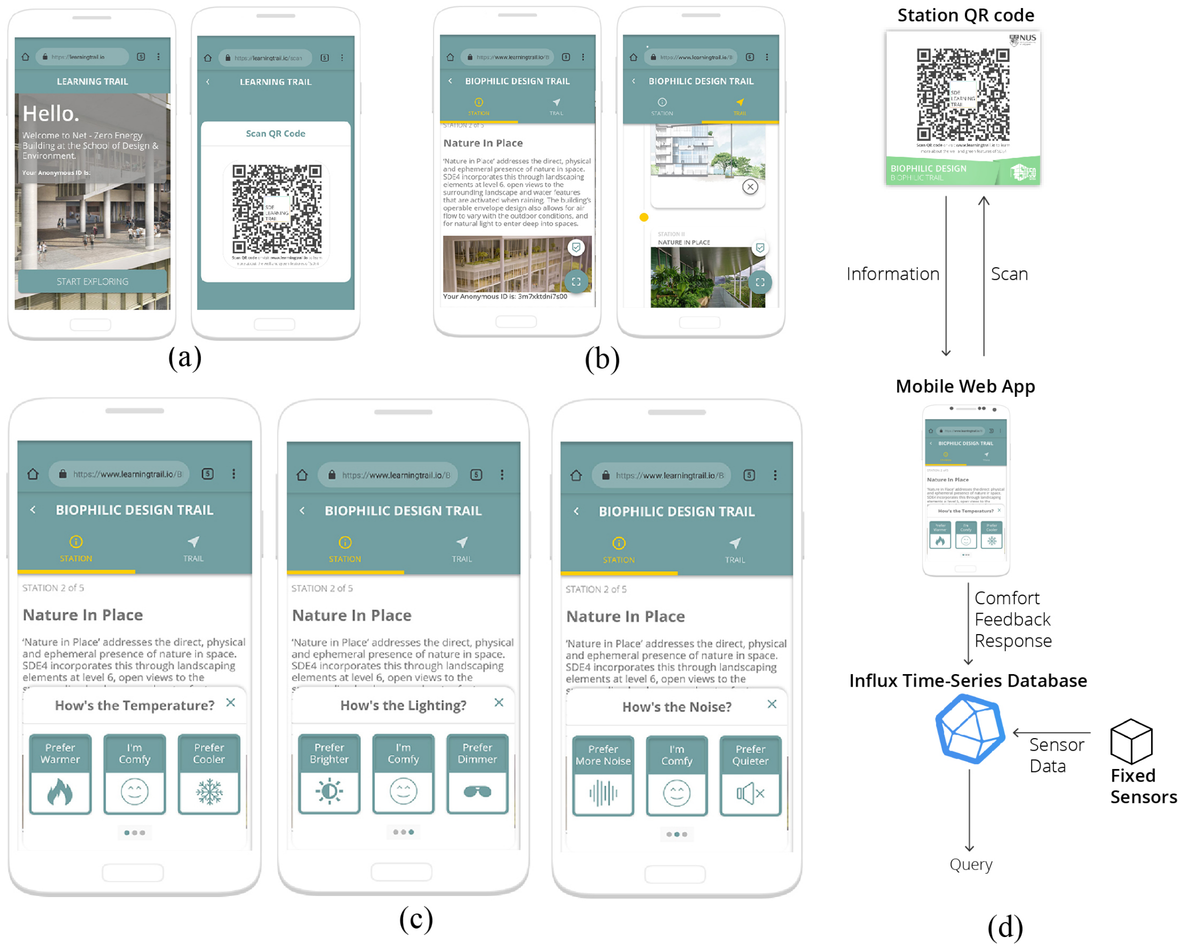

Figure 2: Overview of the Learning Trail app: (a) The welcome screen and an inbuilt QR code scanner capability of the app, (b) Screens for sharing station content and trail configuration with the users, (c) In-built feedback prompts: Temperature - *Prefer Warmer, Comfy, Prefer Cooler*, Light - *Prefer Brighter, Comfy, Prefer Dimmer*, and Noise - *Prefer Louder, Comfy, Prefer Quieter*, (d) Overview of data acquisition platform

differences in user *preference personality types* based on the clustering. For instance, type A prefers quieter spaces as compared to others, whereas B prefers quieter surroundings. Type C prefers bright and cool spaces, type D is mostly comfortable with any condition and type E prefers a mix of conditions, adjusting preferences but mostly comfortable with light levels. Understanding and defining these differences between user types can be used to personalize spatial recommendations to individual users based on their past preferences. Its important to note that Individual user feedback was clustered using unsupervised learning techniques. We used Ward's method for hierarchical clustering based on euclidean distance.

4. Discussion

The results give a preliminary understanding of the unsupervised segmentation of occupants into similar behavior cohorts. While these insights are limited in the traditional comfort modeling perspective, several key conclusions were discovered that lead to future investigations.

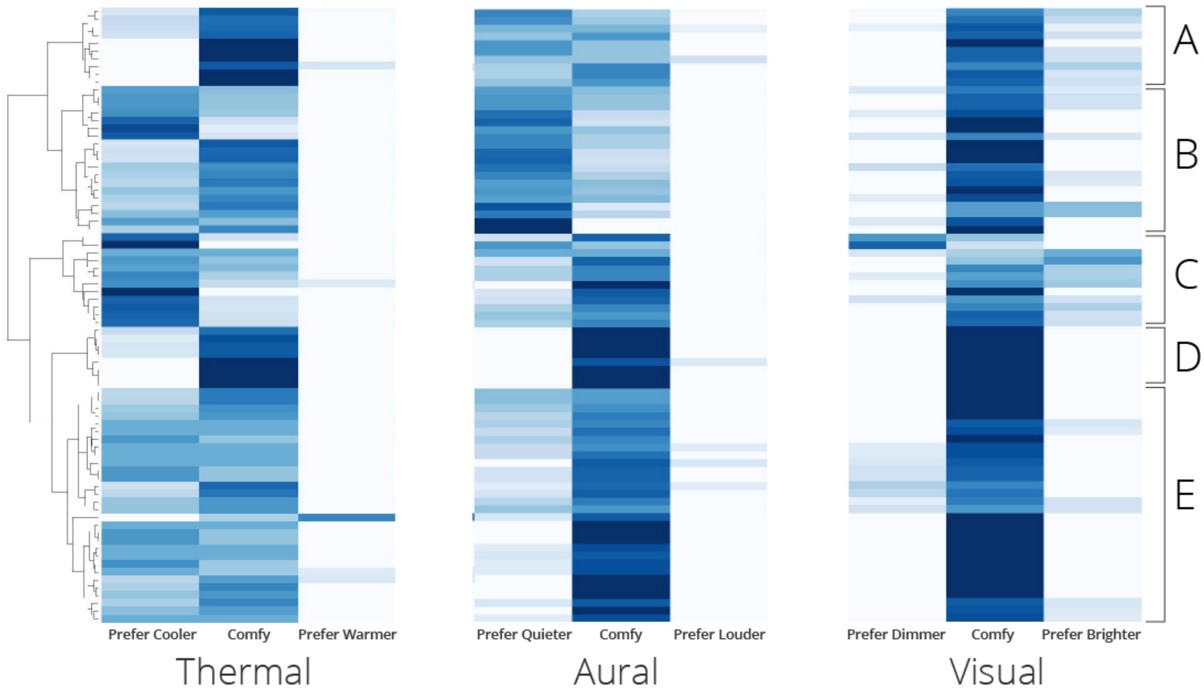

Figure 3: Indoor and outdoor comfort preference clustering: Users are grouped based on comfort preferences: A) Prefers quieter spaces compared to others, B) Prefers cooler and quieter spaces, C) Prefers brighter and cooler spaces, D) Mostly comfortable, E) Preferences of this type keep changing as compared to others but they are usually comfortable with light levels

4.1. Choice of a field based experiment setup

The first aspect of this study is that it is field-based. The goals for conducting comfort assessments under controlled lab settings can be different from conducting the same in field conditions. The former is better suited for dispositional approaches - where the surrounding environment doesn't effect participant behavior, whereas the latter is focused on situational approaches - where behavior is dependent on the surrounding context. Given that the one of the aims for this study was to understand the dynamic nature of occupant comfort in different environmental and spatial contexts, the research team chose a field based experiment setup to provide higher ecological validity to the findings compared to a lab experiment [6]. It was determined that field-based conditions can result in a higher volume of feedback, which is useful in capturing behavior and preference in a scalable way.

4.2. Findings from large data and a 3-point preference scale

Generalizing findings for the larger population using detailed surveys or interview results from a small group of participants was a trusted method for comfort assessments in building research in the past. However with new technologies and modern data capabilities, collection, processing and analysis of large data sets has become easier. That's why this study utilizes QR codes, an interactive mobile application and time-series database infrastructure to collect and process a relatively large comfort assessment data set in a short time. As highlighted earlier in Section 1, comfort feedback data can be skewed due to a participant's personal traits, geographical and cultural background and response biases. To limit subjectivity and make it easy for participants to provide feedback in field conditions, the team used a 3-point comfort scale rather than the traditional 7-point comfort scale. This not only saved participant's effort and time in the field but also helped channelize and organize data streams for the research team easily.

4.3. Identification of occupant types

This study identifies personalized comfort profiles of users through data driven methods - which basically cluster users into *types*. This could be used to understand, and even predict, patterns and anomalies in occupant behavior and occupant profiling in the future. Its easy to see how the same methodology could be used to distinguish spaces based on occupant comfort feedback data - to derive comfort profiles of spaces.

4.4. Limitations

It is important to note that the SDE4 building is operational, but still under a defect and liability period. Since a majority of the new building's systems are still undergoing calibration and refinement for full operations in the future, multiple data sources are not integrated into this analysis. This analysis is preliminary and further convergence of data from these other sources such as fixed environmental sensors, demographic information, and physiological information from wearable devices will produce more traditional comfort modeling insight.

5. Conclusion

This paper describes the pilot implementation of Learning Trail application at the new building in NUS for occupant comfort data collection. Within just three months, 1163 environmental feedback momentary assessment surveys of thermal, visual and aural comfort were obtained participants who gave five or more votes. A total of 616 participants have contributed to the study till date, with minimal administrative overhead. This rich data set provides new opportunities for understanding occupant comfort behavior through data driven methods. Within this study, we've demonstrated how data can be used to group occupants into comfort profile types and shown this study as potential stepping stone to other research areas such as comfort profiling of spaces, occupant behavior analysis and correlation identification between various spatiotemporal variables in buildings.

5.1. Reproducibility

Segments of the raw data and analysis code used in this analysis will be availabe in an open-access Github repository that includes documentation on the Learning Trail app. The app is a mobile, web-based platform that can be deployed in other locations in collaboration with the authors.

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