Self-Learning Framework for Personalised Thermal Comfort Model

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Self-Learning Framework for Personalised Thermal Comfort Model

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Abstract: This paper presents a novel self-learning framework for building personalised thermal comfort model. The framework is built with the understanding that each occupant has a unique thermal comfort preference. Current thermal comfort models focus on analysing average data for groups of people in different types of building, rather than considering individual thermal preference. We argue that building a personal level comfort model using learning algorithms may provide the basis to represent personalised dynamic thermal demands. By bringing more personal interest and data, the ground-up personalised model may help us better understand the internal links of personal factors from psychology, physiology and behavioural aspects. Furthermore, we developed an Smart Thermal Comfort (STC) environment sensors and mobile application to efficiently collect distributed personal data and make it open-sourced for other researchers to use. The aim of this paper is to rethink current comfort studies to standardize the methods in modelling personalised thermal comfort. By summarising the past five years' papers on personal thermal comfort model, this paper critically evaluates the methods used for personal data collection and learning algorithms. Finally, we conclude an Personal Thermal Comfort (PTC) framework including distributed personal measurement tools and machine learning algorithm for personalised thermal comfort study.

Keywords: Personal thermal comfort, adaptive behaviour, machine learning, digital data collection tool.

1. Introduction

At present the definition of Predicted Mean Vote (PMV) is based on large population statistical laboratory studies (Fanger, 1970), as a standard in ASHRAE 55 and ISO7730, and is widely used in Building Energy Simulation (BES) programs all over the world. However, many studies show that the PMV model has been unsuccessful in representing occupants actual thermal sensation vote (Yang and Zhang, 2008; Daghigh et al., 2009; De Dear et al., 1998; Humphreys, 1978; Deuble and de Dear, 2014). The emerging adaptive thermal comfort model which considers occupants' behaviour as an important factor has therefore become a more popular method to meet the dual targets of occupant thermal comfort and energy efficiency (De Dear et al., 1998).

However, most of these studies focus on modelling based on average group data statistics and ignore the localised or personal thermal preference differences at individual levels (Jazizadeh et al., 2013; Jiang and Yao, 2016; Y. Zhao et al., 2014; Auffenberg et al., 2015). In other word, there is a gap between individual and group level thermal comfort requirements. At the same time, as the rapid development of the concept of "smart home", such as thermostats from Nest, Ecobee, Netatmo etc., the thermal demand from home or personal level also increase the importance of building comfort model for small groups of people or individuals. Based on this gap, recent papers proposed different individual thermal sensation models which are appropriate for different types of building (Auffenberg et al., 2015; Jiang and Yao, 2016; Gao and Keshav, 2013; Q Zhao et al., 2014; Liu et al., 2007; Jiang et al., 2017). In relation to the sample size or model applicability, fundamental studies are still needed to clearly examine how the individual personal thermal comfort model is produced and how to apply it into Building Energy Systems.

The outcome of this paper is the proposal of a self-learning framework for personalised thermal comfort model. Under this framework, this paper critically discusses current personalised comfort studies in three parts: the importance of personal thermal comfort model, next generation data collection tools and learning algorithms comparison. First, based on thermal regulation system, we critically evaluate the position of PMV and adaptive model. By suggesting treating personal model by narrow and broad sense, we analysed the importance of individual difference and its potential requirement for data collection tools. Second, the way occupants interacted with the built environment is challenged by different digital data collections tools, especially personal measurement. For example, mobile apps have the function of positioning, wireless data transitioning and easy-to-use user interface which could profoundly decrease data collection difficulty and increase data diversity. We listed several commonly used devices, compared them with some latest digital technology and summarised some new possibilities in personal comfort modelling. Third, by reviewing several latest personal comfort algorithm studies, we introduced three basic machine learning algorithms: Logistic Regression, Support Vector Machine and Artificial Neural Network.

2. Why personal thermal comfort model?

Currently, personal comfort models are commonly built to cooperate with Personal Condition System. In PCS, energy is only deployed in the space where thermal comfort is needed (Veselý and Zeiler, 2014). It is configured to fit individual needs and have been tested with good energy efficiency results (Kaczmarczyk et al., 2010; Pasut et al., 2013; Zhai et al., 2013), especially for residential building (Veselý and Zeiler, 2014). However, in recent years, increasing studies start to focus on using personal thermal comfort to solve general comfort problems (Jiang and Yao, 2016; Kim et al., 2017; Qianchuan Zhao et al., 2014). Instead of just modelling within individual level, personal thermal comfort could also be used as a foundation to simulate behavioural-based human interaction and applied to building energy management system (Jiang et al., 2017). But before building extraordinary model, it is necessary to carefully think about why we need personal comfort model and how to scale it.

2.1. PMV and Adaptive Model

PMV and adaptive model are still two main models used in thermal comfort. PMV is made based on static steady laboratory experiment by Fanger in 1970 and widely applied in HVAC buildings around the world. However, there are many studies shows that PMV underestimate or overestimate occupant’s thermal sensation. In the contrast, in adaptive model, occupants are treated as active agents which could interact with surround environment instead of just a passive receiver (Brager and de Dear, 1998). Compared with PMV, people should have more power to dominate the thermal environment within a certain level, except when weather variations exceed the thermal threshold human could control. However, there is still controversy between PMV and adaptive model. Because PMV still serves well for HVAC system building and adaptive still have quite a lot limitation when apply it in the real world. Many studies focus on how to compare PMV with adaptive model in different building types, countries, applied to different people with various age, nationality and gender. These really help researchers build a better worldwide database, but it is time to rethink what kind of thermal comfort model could succeed simulating person's adaptive thermal comfort.

Based on the concept of self-regulating thermal comfort system (Nicol and Humphreys, 1973) and adaptation feedback loop (De Dear et al., 1998), within indoor environment and ignore any potential factors such as lighting, acoustic and material factors, the entire thermal regulation system could be generally described in Figure 1:

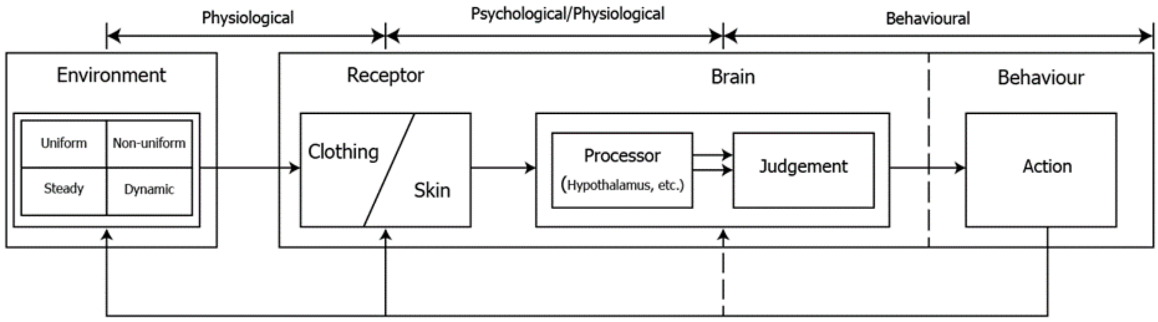

Figure 1. Thermal regulation system

From the environment which decides occupant's initial objective conditioning level, the physical cognition signal is produced on receptors (generally skin or clothes) and transport to the hypothalamus. Different kinds of receptors or sensors embedded under the skin and tissue give people the ability of passing the perception information. This is how perceived information transformed from external to internal. When hypothalamus got the information, it will deliver the electrical impulse to different lobes in the brain to process the signal and form a general judgement. Fanger's work is mainly explained the relationship between the perceived information and the judgement result. However, adaptive process covers more parts. When you have a judgement, you may/may not have an action which expressed by behaviours to change current environmental. It could be a gesture which turn-on the air conditioner to make yourself cooler (response to environment), an action that put on a jacket to make yourself little warmer (response to receptor) or a period of silence which make yourself calm down (response to brain). The systematic running of these four modules could generate a complete thermal sensation feedback loop, a "reflex arc".

In general, studies always like to talk about PMV model and adaptive model separately. However, if we systematically analysed them from the process that how information was transferred through this "human" and "environment" feedback cycle, PMV and adaptive model are not quite "different". In our view, there is not absolute right or wrong between adaptive and PMV model. It could be treated as a "scale" problem in thermal regulation system. PMV model mainly focus on exploring the configuration which linking environment, receptor and brain while adaptive model considers the entire cycle system which includes the feedback influence of behaviour. They have different scales and result, but within the same logical cycle. In addition, to personal comfort model, it proves that in the view of physiology, each person has a unique feedback loop process based on physical neural network.

2.2. narrow and broad sense of personal thermal comfort

In this feedback loop, the personal thermal regulation system is influence by many factors from psychology, physiology and behaviour, the term "personal" could also be defined by narrow and broad sense. The narrow-sense personal model is just a thermal comfort model for a single person within a certain area, or we could call it a private room. There is no any other people in that space to indirectly interact with and the model is only built for this person. The place could be in a bedroom, a capsulated office room etc. In contrast, the common-sense personal model is built in a more complex environment, with surrounding people, with social interaction and dynamic context, where the other factors all may influence the assessment of a person's thermal comfort. For instance, assuming there is a thermal comfort field study that conducted in an office building with 20 subjects. During three weeks' study, each subject need to finish questionnaires three times a day. Subjects work together in the same office; their context and cognition have been interacted with each other. Although finally each subject still got amount of data, this data is just a broad-sense personal data. If want to get narrow-sense personal data, each subject should be simultaneously isolated in a similar office.

Most of the field studies don't carefully pay attend to the difference between narrow-sense and broad-sense setting. As a result, it is better to separate these two types of personal concept in real studies. Because it is always difficult to represent broad-sense personal thermal comfort under the influence of context and following cognition variation. Starting from narrow-sense personal thermal comfort and then apply to different scenarios could be the key to fundamentally quantify and validate the adaptive process in real field study.

2.3. Individual difference

Individual difference is commonly referred in psychology studies, especially in differential psychology. Psychology is a study of individuals, but modern psychologists often study groups, or attempt to discover general psychological processes then apply to all individuals. They always treat variation as error rather than take it as interesting phenomena to study. But the fact is that there are significant variations between individuals and it is important when we want to explain how variant behaviour differ.

In comfort study, behaviour adjustment, physiological acclimatization and psychological habituation are three sections which produce huge influence on adaptive process. There are some studies (Gauthier and Shipworth, 2015; Wei et al., 2010) summarise which kinds of behaviours that occupants more likely to engage. But there are still huge sampling error and applicability to generalize those methods to comfort studies. A common method during their field study is increasing personal interest to achieve more meaningful analysis. In addition, personal comfort model is a dynamic process. There are much valuable details are missing in conventional comfort field study. In order to take care of all these factors, increasing personal interest is a good way to generalize more accurate data for specific comfort studies.

2.4. Rapid growing technology

Personal thermal comfort model also brings a question that "Are current sensors and questionnaire technology possible to measure such increasing personal interest?" Personal comfort measurement not only require environment, body, perception and behaviour data, but also need to collect all these data simultaneously, accurately and efficiently. Compared with widely used data logger, handheld sensors or different kinds of digital questionnaires, to accomplish personal thermal comfort measurement require a high-level facility which could be a big automation challenge. In recent years, there appear several advanced data collection tools which take advantage of new technologies such as Bluetooth Low Energy (BLE), hub or mobile app (Gao and Keshav, 2013; de Dear et al., n.d.; Zhao et al., 2017). Instead of conducting repetitive studies on changes in thermal sensation, these new data collection methods could easily track real-time environment data, thermal responses and adaptive behaviour. It is not only a challenge for researchers, but also a job for engineers to develop new measurement sensors with reliable calibration method.

3. PTC Framework

The framework for Personalised Thermal Comfort (PTC) model is based on the principle that each person has their unique dynamic comfort model. As personal comfort data could be treated from common or narrow sense, this framework focus on narrow-sense personal modelling, which keeps the subject away from psychological or behavioural influence from other people. Figure 2 illustrate how personal thermal comfort framework works.

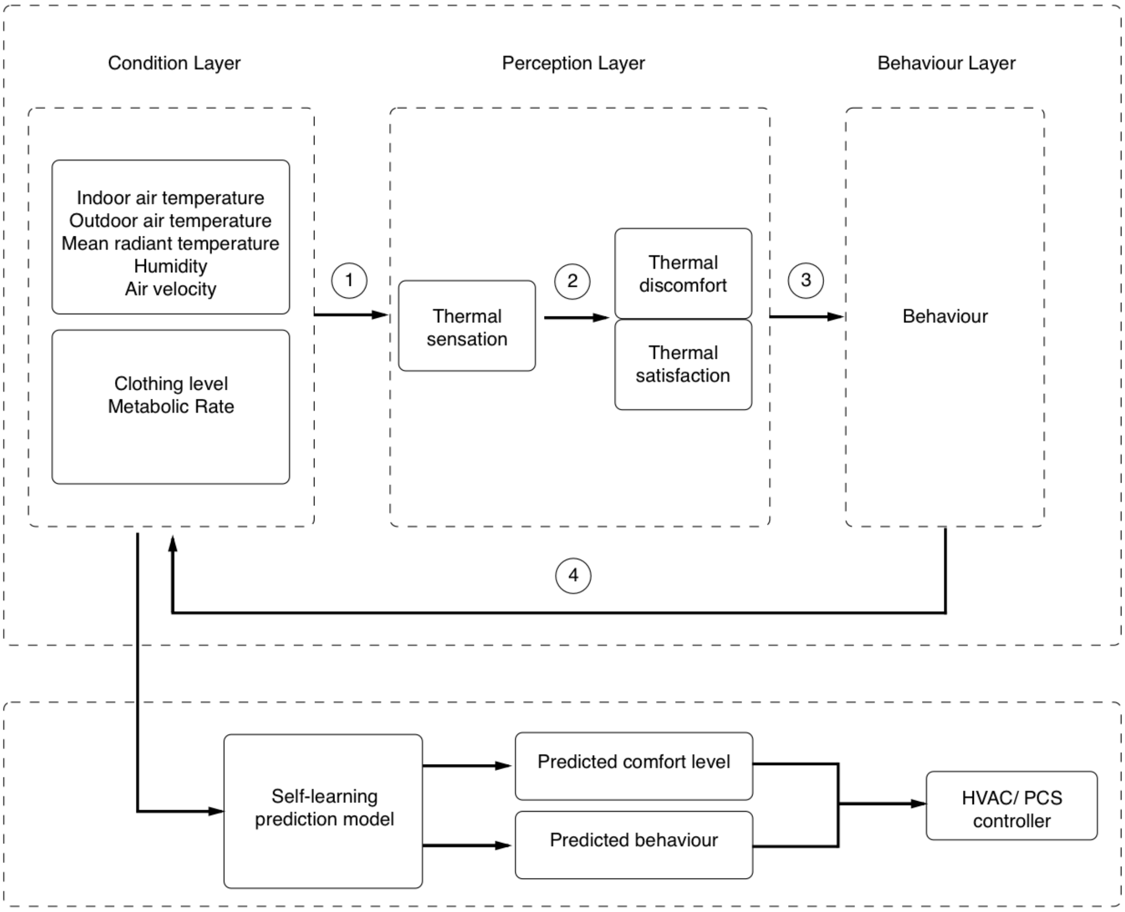

Figure 2. Self-learning framework for personalised thermal comfort (top), self-learning implementation in HVAC/PCS system (bottom)

In PTC framework, there are four steps, or so called four functions. Firstly, perception function. The environment data including outdoor air temperature and personal data which considered as "Condition Layer" are perceived by skin receptor and produced initial thermal sensation. Secondly, habituation/acclimatization function. Any factors including subject's previous experience, genetic reason, stress could be counted into this function. As there are so many possible ways to systematically arrange this function, this framework treat thermal sensation, discomfort and satisfaction as a whole system which named as "Perception Layer". Thirdly, behaviour function. From the thermal perception and "attitude" that subject produced, they may or may not conduct corresponding adaptive behaviours. Finally, feedback function. The feedback from the adaptive behaviour will re-influence environmental condition such as opening the window or change personal condition by take on/off clothes until the subject feels neutral or remain at a certain level. For instance, the subject was sitting in his room. But he felt a lit bit warm (perception function). He was not satisfied with current thermal environment (habituation/acclimatization function). So he took off his sweater (behaviour function) and feel much better (feedback function + perception function + habituation/acclimatization function). In addition, if the prediction result of thermal perception and behaviour could be communicated with PCS or HVAC controller. The system will not only give suggested temperature setting based on comfort level, but also considering behaviour change as another option.

To quantify these four steps, it is necessary to clarify which method to use. First, as all the variables in each layer are discrete, the relationship between each layer could be treated as a classification problem. Second, instead of traditional statistics method which based on average data, learning algorithms, especially machine learning algorithms are used in personal adaptive process to deal with individual difference. Finally, depending on the difficulty or research topic you want to achieve, swiftly simplify the variables in each layer. For instance, habituation/acclimatization function contain so much context to control. As a result, we could just use thermal sensation to represent perception layer. Figure 3 shows the details of this learning process:

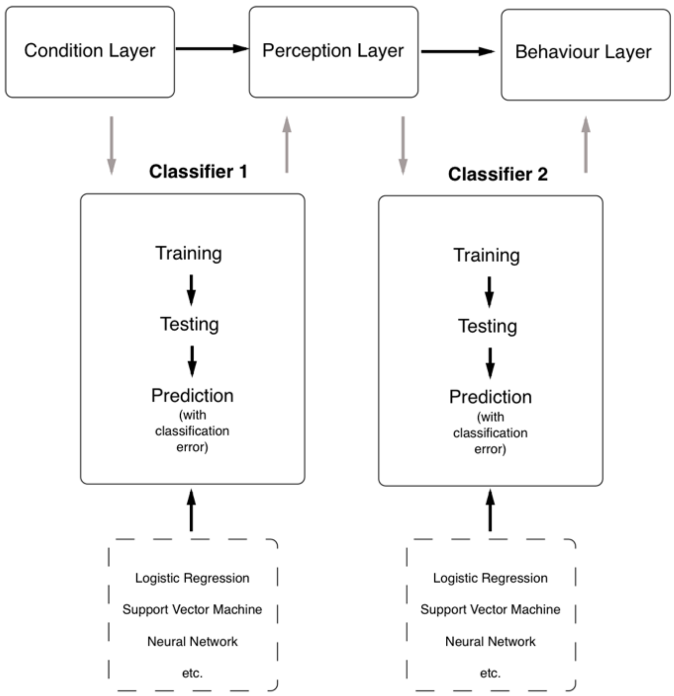

Figure 3. Machine learning process between three layers

Our approach is based on two supervised machine learning steps: “Condition Layer” to “Perception Layer” and “Perception Layer” to “Behaviour Layer”. The logic in these two steps is the same: data import, data training, data testing and finally got a prediction result with its unique error. In each step, different machine learning algorithms will be tested and the best algorithm which achieve the best prediction result with low error will be selected. This also means the final selected algorithm in each step for each subject may not be the same. Finally, each subject will get a unique personalised prediction model which predict his thermal sensation and potential adaptive behaviour.

4. Methods

4.1. Data collection tool

ASHARAE 55 provides a reliable sensors standard for researchers to follow. However, on the market, it is difficult to find a sensor which could cover air temperature, mean radiant temperature, humidity and air speed at the same time. In reality, most of the researchers still put these sensors together and manually record the data and switching different sensor one by one always increase measurement error during real field studies. Some companies or institution could develop this as an all-in-one device, but it cost so much money and the final products are always not quite open to the public. At the moment, one of the most common way to take measurement is still data logger and these sensors lack of connection properties such as Wi-Fi or Bluetooth to provide real-time distance monitoring. Thermal comfort study need a cheap, reliable, open-sourced, smart-connected sensor to conduct more accurate and efficient field study. This paper introduces Smart Thermal Comfort (STC) sensor box (Figure 4).

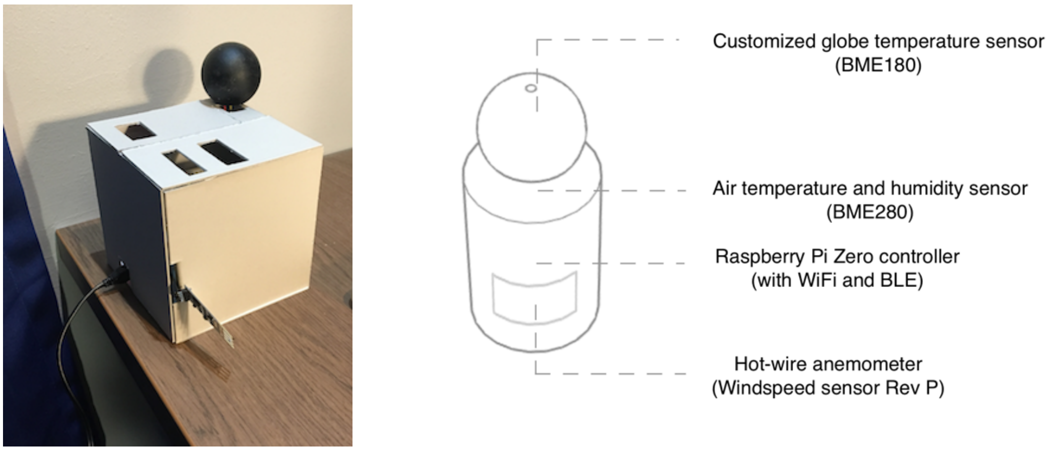

Figure 4. STC sensor box (left) and internal core sensors (right).

STC sensor box is an open-sourced thermal comfort measurement tool. You could visit our GitHub page (https://github.com/jayingq/Smart-Thermal-Comfort-System) to get latest news. First, the sensors are all benchmarked and tested from the current existing sensors on the market. Second, in order to help researchers conduct their own thermal comfort studies, all the source codes of STC are open-sourced (MIT licenced) which means anyone could buy the sensors on the market and make their own measurement tool. Finally, specific sensor settings in the STC systems are totally controllable. The minimum measurement interval could be set as 5s and there is no max limit. In addition, there are many open-sourced libraries (packages) on the Internet which could help you add more function. Table 1 shows the details of the sensors used in STC sensor box:

Table 1. Sensors specifications

Environment parameters	Range	Accuracy
Air temperature (BME280)	-40C° to 85C°	±0.5C° (calibrated)
Globe temperature (BME180)	-40C° to 85C°	±1C° (max)
Relative Humidity (BME280)	0% to 100%	±3%
Wind speed (Wind Sensor Rev P)	0 to 30 m/s	±5% (calibrated)

When the measurement begins, all the data will store in its SD card by CSV file and simultaneously uploaded to our database by Wi-Fi.

4.2. Digital questionnaire

A cheap, all-in-one and open-sourced sensor box is not enough for a well automated data collection system. Based on EdenApp (Zhao et al., 2017), we developed STC app, an mobile application (currently only support Apple device) to conduct thermal comfort digital survey. Instead of paper-based or web-based traditional medium, occupants could use their smart phone, the app to finish all the questionnaire.

Firstly, to improve efficiency, we add experience sampling function. In conventional thermal comfort survey, subject always need to follow the daily goal, such as finish the questionnaire three/four times a day or fill it in the morning, lunch and after dinner. This kind of survey usually take several months or a year to gather enough data. However, there are still many interesting points are missing during the measurement. Figure 5 shows a simple temperature and humidity measurement of a student's accommodation room. If just like a conventional survey which take three times a day on fixed time, it is difficult to detect the dynamic thermal variation marked as red circle.

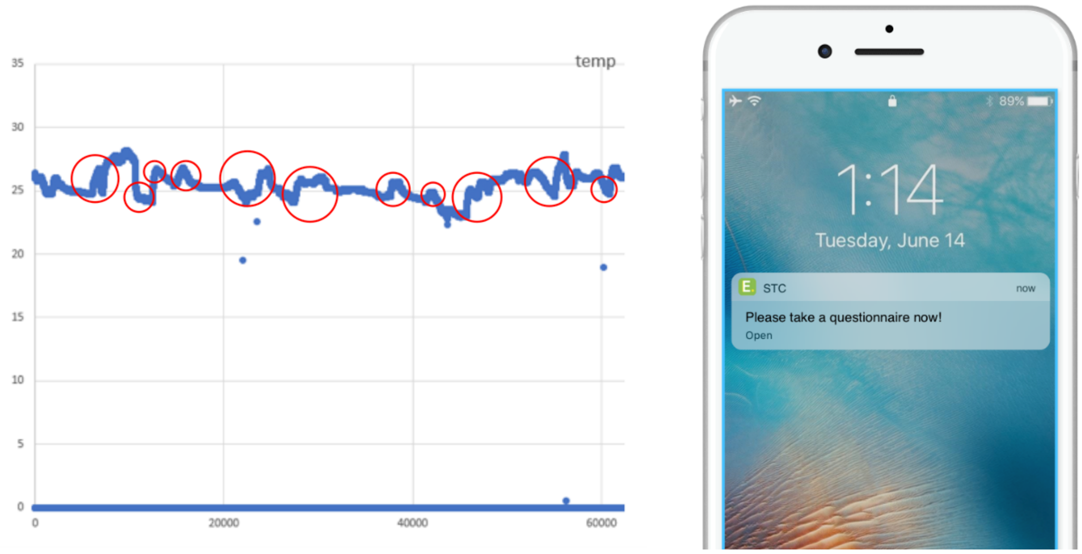

Figure 5. Air temperature variation in a student's accommodation in Edinburgh (left); Notification in STC app (right).

With experience sampling method in STC app, when the temperature in the past ten minutes changed about 0.5 degree (customizable), the app will automatically send notification to the user to take questionnaire. Moreover, ten minutes later, the app will send another notification suggesting subjects to take another questionnaire to examine their corrected thermal sensation and preference. It will really help both researchers and occupants make their work more efficient. Secondly, user-based mobile app could give occupants a more natural way to express their thermal sensation and increase completion rate of the survey. According to our pilot study, it generally takes no more than 30s to finish a questionnaire. Figure 6 illustrates the workflow of the STC app and Table 2 shows the thermal perception and behaviour data collected from the app.

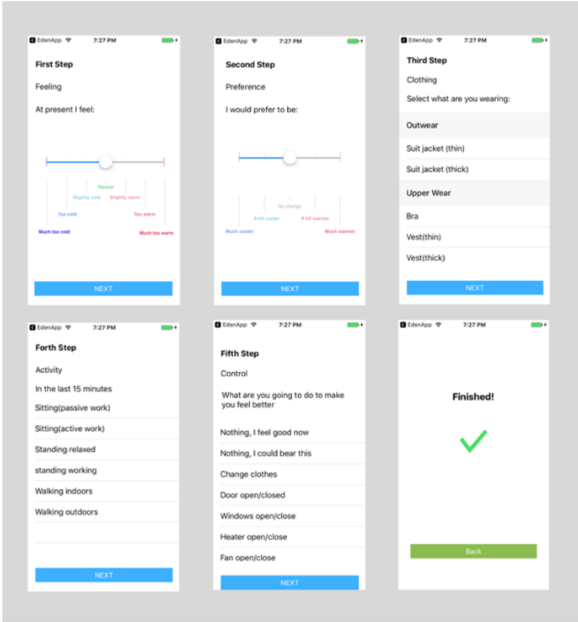

Figure 6. STC App user interface (the latest version may be updated on our GitHub page)

Table 2. Thermal perception and behaviour data collected from STC App

Information	Reference	Scale	Range
Thermal sensation	7-scale thermal sensation vote	1	From -3 to +3: Cold (-3), Cool (-2), Slightly cool (-1), Neutral (0), Slightly Warm (+1), Warm (+2), Hot (+3)
Thermal preference	(Nicol et al., 2012)	1	From prefer much warmer (+2) to much cooler (-2)
Thermal satisfaction	5-point satisfaction scale	1	From very satisfied (+2) to very dissatisfied (-2)
Adaptive behavior	(Wei et al., 2010; Gauthier and Shipworth, 2015)	/	Nothing (0), change clothes (1), adjust door/windows (2), adjust thermal control (3), have food/drink (4), change location/room (5), other (6).

Finally, as ethical problem and data management system, the app cannot upload to App store, but we make it open-sourced and all the source code is available on our STC GitHub page. You can download the source code, customize the app based on your project and run it on your iPhone or iPad.

4.3. Learning Algorithms

After getting all these data, within the framework, how to choose the best learning algorithms decide the final prediction accuracy of the entire model. There have been an increasing amount of study using machine learning algorithm to predict thermal comfort (Kim et al., 2017; Chaudhuri et al., 2017; Jiang et al., 2017; Jiang and Yao, 2016). However, all of them just focus on how to predict thermal sensation vote, but ignore the importance of adaptive behaviour which because of lack of related data on current comfort database. There are many learning algorithms which could be used to build personal thermal comfort model and they always achieve great results. In this section, we simply introduce three of the most commonly used supervised machine learning algorithm for thermal comfort:

a. Logistic Regression
   Logistic Regression is a statistical method dealing with the situation when there are multiple inputs with one outcome. It computes a weighted sum of the input data and uses sigmoid function to output a number between 0 and 1 which stands for its probability. For instance, in personal thermal comfort modelling, thermal sensation is presented by seven scales from -3 to 3. By training seven binary classifiers for each set of input data, Logistic regression could give each scale a probability. Rank the probability list and the best prediction result (sensation level) could be selected.
b. Support Vector Machine (SVM)
   SVM is another commonly used machine learning algorithm for classification. It builds a hyperplane to separates different classes. Meanwhile, to avoid the model over-sensitive to original data, soft margin classification is suggested. By adjusting hyperparameter C to limit margin violation, it could help make fewer prediction error.
c. Artificial Neural Networks (ANN)
   ANN is based on the human biological neuron networks, wherein signals are transported between millions of connected links. The weighted neuron and links perform programmed function to determine output signal. In fact, ANN suite for project which has very large data size and huge complexity. But some studies used it to analyse thermal comfort problem and it may be widely used when there are more data coming in the future. For instance, Chaudhuri (2017) built a two-layer feed forward ANN, with sigmoid function as activation function for hidden and output neurons.

5. Discussion and Conclusion

This paper presents a novel self-learning framework for building personalised thermal comfort models. To simulate personal adaptive process in comfort modelling, STC data collection tool including sensor box and mobile app are developed depending on accuracy, cost, customizability and efficiency. As an open source project, STC data collection tool is a good start to combine digital sensors and smart questionnaire to capture more detail under different scenarios. With more data and reasonable field study setting, it could help researchers better understand adaptive model from personal level and build better prediction model for building energy system.

Personal thermal comfort model is a good start to conduct "ground-up" comfort simulation. In most buildings, space is occupied by multi-users. But narrow-sense personal model only suite for space like accommodation, hotel or personal office, or for PCS. Thermal comfort standard such as existing PMV or adaptive model consider most people's profit, instead of a space with only one person. In fact, personal thermal comfort is the first step to build a full personal comfort profile. Based on this data, how each occupant interacts with each other and how comfort preference varied could be quantified in multi-user space. Figure 7 illustrate how self-learning framework could be used in multi-user space by Agent Based Modelling (ABM). Each subject could be treated as an agent with their own property and function and these functions influence how agents interact with each other. It is a big challenge to model each agent (Jiang et al., 2017) and hope this personalised thermal comfort self-learning framework could help build the foundation of this complex simulation.

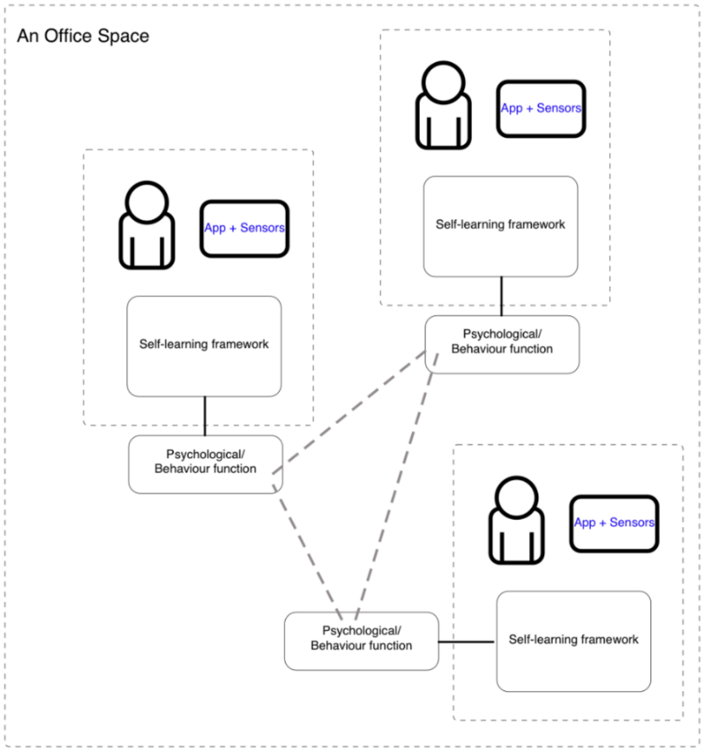

Figure 7. Thermal comfort interaction and variation in multi-user space (office)

In the future, there are a lot of work to do based on personalised thermal comfort to better understand human thermal adaptive process:

a. By tracking the same group of people, find out whether or how building types influence personalised thermal comfort.

b. Conduct the field study with more subjects.

c. By using more dynamic environment setting to increase prediction range of comfort level and behaviour.

d. Try ABM to simulate and validate how personalised thermal comfort vary in a social context.

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