

**NANYANG
TECHNOLOGICAL
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SINGAPORE

**Human and Indoor Environment Interaction
through EEG-based Methods and Implications in
Life Cycle Perspective**

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School of Civil and Environmental Engineering

2018

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School of Civil and Environmental Engineering

**A thesis submitted to the Nanyang Technological
University in partial fulfillment of the requirement for the
degree of Doctor of Philosophy**

2018

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Summary

This research has the long-term vision that the wellbeing and work productivity of building occupants should be incorporated into the more balanced building design and operation. To achieve this vision, the thesis focused on improving the understanding and implementation of the two-way human-building interaction, i.e. the impact of indoor environment (thermal environment and indoor air quality) on occupants and occupants' feedback to the building. The core of this research established EEG (electroencephalogram) based methods for a potentially more accurate and objective human-building interaction. Specifically, the impacts of indoor environment on occupants' wellbeing and performance were more objectively and accurately quantified by EEG indices, namely asymmetrical activity and frequency bands. These indices also helped to explain and correlate with traditional subjective indicators and task-based indicators. Machine learning-based EEG methods in human-computer interaction domain were also explored in this research. Together with EEG indices, the machine learning-based EEG methods can be the main feedback mechanism of wellbeing and performance to the building. Furthermore, the incorporation of the wellbeing and performance of occupants into the building life cycle platform was also explored and extended to other building types other than office buildings, namely the educational buildings. Both a better human-building interaction through EEG-based methods and the perspective through life cycle platform can contribute to the incorporation of occupants' wellbeing and performance into the more balanced building design and operation.

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Chapter 1 Introduction

1.1. Background

Today, people on average spend up to 90% of their time in buildings, including offices, factories, schools, or homes (US EPA 2011). This means that the indoor environmental quality (IEQ) of the building must be satisfactory enough to provide comfort, enhance work productivity, and maintain general wellbeing of the building occupants. As the report “Health, Wellbeing & Productivity in Offices” (World Green Building Council 2014) puts it, “green”, or environmentally friendly building is often associated with low carbon footprint and efficient energy consumption. However, this might not necessarily mean a green building could improve wellbeing and work productivity of the occupants. Green technologies and policies generally focus on reducing impact on the environment, while neglecting the fact that the main purpose of the building is to cater to the welfare of occupants. For instance, the current green building rating system in Singapore (BCA Green Mark scheme 2009) focuses mainly on the energy and resources efficiency aspects, while the occupants’ wellbeing and performance are scarcely considered. Existing guideline such as ASHRAE Standard 62.1 (2010) also recommends the minimum ventilation rates in buildings, but these minimum thresholds are often not sufficient for occupants’ wellbeing and performance. Therefore, a holistic sustainability assessment of buildings should also include impact on wellbeing and work productivity of occupants in the long term.

1.1.1. Impact of indoor thermal environment on occupants

One important aspect of IEQ is the indoor thermal environment, and its impacts on occupants have been studied extensively during the past few decades. Fanger initiated the study of thermal comfort using the questionnaire-based predicted mean vote model (Fanger 1970), which has been developed subsequently by many

researchers undertaking chamber studies and field studies. Based on these studies, ASHRAE Standard 55 provides recommendations to thermally comfortable indoor environment, by considering the combined effects of temperature, humidity, air speed and human factors including clothing and metabolic rate (ASHRAE Standard 55, 2013). In addition to thermal comfort, studies also investigated the impacts of thermal environment on other subjective perceptions such as perceived air quality, sick building syndromes and perceived work performance (Seppanen et al. 1989; Mendell et al. 2002; Fang et al. 2004), and the main conclusions were that these self-perceptions would generally deteriorate when thermal environment is out of thermal comfort zone, especially on the warmer side (Zhang et al. 2011). Apart from subjective questionnaire-based studies, objective human productivity studies are also extensive. Objective human productivity under different thermal environment has been quantified by performance of lab-based cognitive tasks such as memory/computation tasks (Lan et al. 2010; Lan et al. 2011; Pilcher et al. 2002), or field-based observations such as the number of phone calls in call centers (Niemela et al. 2002). For effects of temperature in particular, the literature review by Seppanen et al. summarized the task performance decrements as a U-shape function of temperature, which showed that performance was relatively worse when the temperature was either too low or too high (Seppanen et al. 2005).

Physiological indices have also been utilized to quantify the impacts of thermal environment on occupants, including skin temperature, heart rate, respiration ventilation, blink rate, end-tidal partial CO₂ (ETCO₂), arterial blood oxygen saturation (SPO₂), biomarkers in saliva and tear film quality (Lan et al. 2011; Tham et al. 2010). These indices were also used to establish the correlations of physiological measurements with subjective perceptions and objective task performance. Electroencephalogram (EEG) is an electrophysiological method to measure electrical activity of the brain. Sensors are attached to the scalp to measure

the electrical signals produced when brain cells send messages to each other. Yao et al. (2008) and Lan et al. (2010) used bipolar method to investigate impacts of indoor temperature on EEG signal, and concluded that the power of various EEG frequency ranges were different under various temperatures. More advanced physiological method such as functional magnetic resonance imaging (fMRI) has also been used to study brain activities for thermal comfort (Kanosue et al. 2002). The main problems for many of these methods are that they are either too cumbersome to implement in practice (e.g. arterial blood oxygen saturation (SPO₂), biomarkers in saliva), or they may not be sensitive enough (e.g. heart rate). Furthermore, many of these methods only measure a specific type of physiological response and may not be extended to other environmental settings.

1.1.2. Impact of indoor air quality on occupants

Another important aspect of the IEQ is the indoor air quality. Better indoor air quality in buildings is often achieved by higher ventilation, which removes bio-effluents and other indoor air pollutants. The outdoor air supply rate is often used as an indicator of indoor air quality, and the minimum rates for different building types have been recommended by the ASHRAE Standard 62.1: Ventilation for Acceptable Indoor Air Quality (ASHRAE Standard 62.1-2010). The impacts of ventilation rate on subjective perceptions have been studied extensively. A literature review by Seppanen et al. showed that when the ventilation rate was below 10L/s-person, the perceived air quality would deteriorate and the sick building syndromes (SBS) would increase (Seppanen et al. 1999). This review study also suggested that the risk of SBS would reduce significantly when the CO₂ concentration was below 800 ppm. A further literature review by a European multidisciplinary scientific consensus meeting suggested the risk of SBS and short-term sick leave could further reduce when the outdoor air supply rate increased up to 25L/s-person (Wargocki et al. 2002).

The effects of ventilation rate on work performance have also been studied. The same review study by Wargocki et al. indicated that the performance of office work could increase when the outdoor air supply rate increased up to 25L/s-person (Wargocki et al. 2002). Other studies also found that the task completion speed could increase in call centers (Tham 2004; Wargocki et al. 2004) with higher ventilation rates, or in school (Wargocki & Wyon 2007) with higher ventilation rate. Furthermore, Wyon (2004) summarized from studies that the simulated works performance could significantly increase by removing the common indoor sources of air pollution such as floor covering, personal computer and used supply air filter, or alternatively by increasing the outdoor air supply rates. Wyon indicated that these studies showed the effects on performance could either be related to subjective perceptions, or could still be present even at pollutant levels that had no measurable effects on the subjective perception of air quality.

1.1.3. Human-building interaction and machine learning

In addition to the impacts of IEQ on occupants, mechanisms of occupants' feedback to the buildings have also been explored to further improve the welfare of occupants. These mechanisms complement to the two-way human-building interaction loop, which comprises both the impacts of indoor environment on occupants and occupants' feedbacks to the indoor environment. One example to create such feedback mechanism is the development of personalized ventilation (PV) system, which allows occupants to actively adjust their immediate zones (Melikov 2004; Yang et al. 2010; Sekhar et al. 2005). For the centrally controlled indoor air conditioning systems, the major feedback mechanisms are still subjective questionnaire-based methods. For instance, some researchers have developed a web-based survey and accompanying online reporting tools to obtain feedbacks from occupants, including IEQ questions such as thermal comfort, indoor air quality, lighting, and acoustics (Zagreus et al. 2004). Jazizadeh et al. (2014) further

proposed a framework to integrate building occupants into the air conditioning system control loop, which controlled the air conditioning system based on occupants' personalized thermal comfort votes in addition to data collected from various environmental sensors. However, the subjective survey-based methods lack certain objectivity and are prone to perception biases. In general, studies in this field are rather limited.

The general human-building interaction is also an emerging subject studied by architects and engineers, who have seen digital information elements incorporated into the fabrics of buildings as a way of creating environment that meets the dynamic challenges of future habitation, with the vision of continuing ubiquitous computing embedded in the world around us (Dalton et al. 2016). The basic idea behind is to apply the human-computer interaction (HCI) concepts and methods to building design and operation, and consequently to improve the human-building interaction. Improving the human-building interaction also highlights the importance of collaboration of disciplines including biological, social and physical sciences, and engineering (Godfrey 2010).

One potential way to improve human-building interaction is to utilize machine learning based EEG pattern recognition methods, which are commonly used for HCI in EEG emotion studies (Esfahani et al. 2011; Frantzidis et al. 2010; Picard et al. 2001) and EEG mental workload/vigilance studies (Gevins et al. 1998; Berka et al. 2004). The machine learning based EEG pattern recognition methods are widely studied in the HCI domain, and have the potential to be further incorporated into the two-way human-building interaction. The essential idea of machine learning is to train a classifier with known data (i.e. the specific classes of different training data are already known), and this classifier will then be used to classify unknown data according to certain rules (i.e. to predict the classes that the unknown data belong

to). Classes in the current context can be thermal levels or air quality levels. Many of the current EEG devices are wearable and wireless, which make the EEG methods more practical. Furthermore, EEG measures brain activities, which can directly reflect wellbeing and productivity.

1.1.4. Building lifecycle assessment platform

On the scale of whole building, the inclusion of wellbeing and work productivity of building occupants also needs to be more appropriately evaluated together with other aspects of building (e.g. with operational energy or building facilities). This will provide a comparing basis for different aspects of building and a guide to more balanced building design and operation. Figure 1.1 shows a conceptual model that addresses this issue (Seppanen and Fisk 2005). In this conceptual model, the costs of all measures that could improve the indoor environment were identified and monetized. Then the corresponding benefits of occupants' wellbeing and work productivity due to better indoor environment were also identified and monetized. Finally the costs and benefits were compared to ensure a more balanced building design and operation.

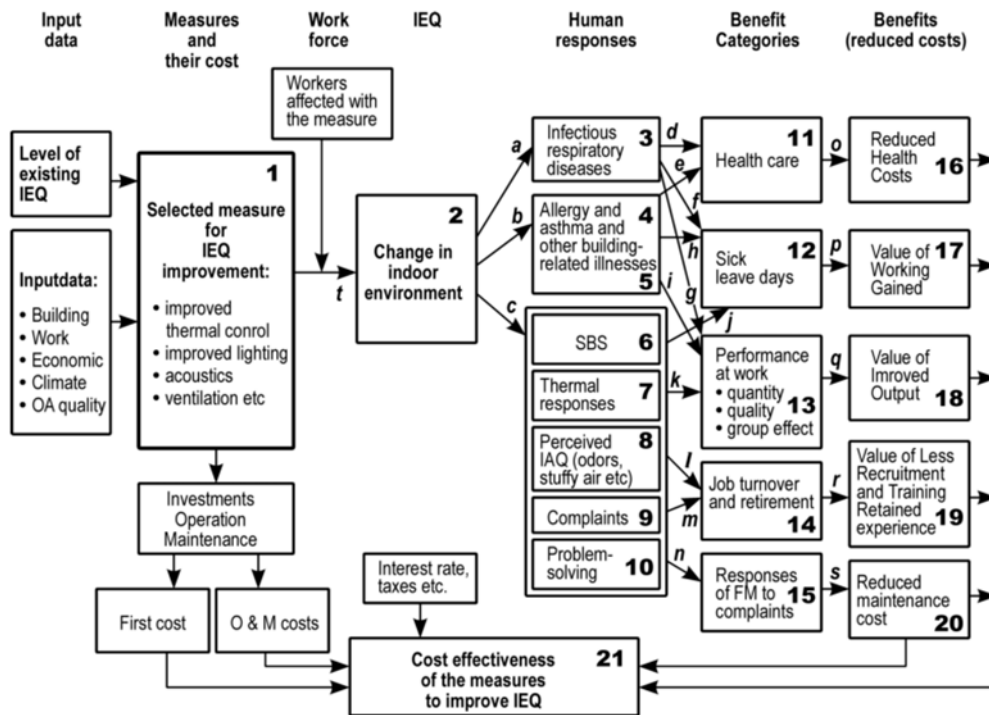


Figure 1.1 A conceptual model of costs and benefits in indoor environment (Seppanen and Fisk 2005)

One suitable assessment tool to evaluate these costs and benefits is the life cycle assessment (LCA) platform. LCA is an approach to analyze the environmental impact of products or activities throughout the life cycle stages, and the International Organization for Standardization (ISO) specifies the details of conducting an LCA, including goal and scope definition, life cycle inventory (LCI), impact assessment, and result interpretation (ISO 14044:2006). As LCA lacks an economic dimension, a parallel framework is often introduced to make different metrics in LCA more comparable in the form of economic or financial LCA (also called life cycle costing, LCC), which monetizes metrics in LCA over the lifetime and discounted to current values (Hoogmartens et al. 2014). There are already quite many studies that have investigated wellbeing and work productivity through the building life cycle perspective, and these studies mainly focused on the office buildings' indoor environment and the corresponding cost-benefit metrics in LCC framework (Fisk 2000; Wargocki et al. 2005). These studies suggested that the

benefits of improved wellbeing and work performance often far exceeded the costs to improve the IEQ.

1.2. Objectives and methodologies

The long-term vision of this research is to incorporate the wellbeing and work productivity of occupants into more balanced building design and operation. Various ways can help to approach this long-term vision. For instance, improved understanding and implementation of the two-way human-building interaction can contribute to this vision. Furthermore, the evaluation of different aspects of the human-building interaction through the life cycle platform can also contribute to this vision. The current main problems are:

- a) The impact of indoor environment on occupants: for the studies utilizing questionnaire-based or task-based methods, the suggested thresholds of indoor environmental indices vary significantly, and many of the results are still quite vague and not clearly understood. The main problems are that the results of questionnaire-based method are prone to perception biases, and the results of task-based method also vary significantly depending on the types of tasks used. Physiology-based method has been used in the hope of quantifying the impacts more objectively i.e. avoiding the perception biases, but many of these physiology-based methods are very cumbersome to implement, and may not be sensitive and clear enough.
- b) The mechanisms of occupants' feedback to the buildings: for the centrally controlled indoor air conditioning systems, the questionnaire-based feedback methods still lack certain objectivity. Furthermore, work productivity of occupants and its optimization cannot be considered in this type of feedback mechanism because traditional methods of task-based evaluations and many physiological measurements mentioned above cannot be incorporated into

the human-building interaction loop due to difficulties to be implemented on a routine basis in real-life.

- c) The life cycle platform: the results of existing building life cycle studies that incorporated the environmental impacts on occupants' wellbeing and work productivity vary significantly, mainly because the environmental impacts that are used for calculation vary significantly among studies as illustrated in problem a). Furthermore, the existing studies focus on very limited building type, i.e. office building.

Therefore, three objectives are established to contribute to the long-term vision of this research:

- To quantify the impacts of indoor environment on occupants' wellbeing and work productivity more objectively and accurately.
- To feedback the impacts on occupants' wellbeing and work productivity to the building more objectively and accurately.
- To extend the evaluation of occupants' wellbeing and work productivity through the building lifecycle platform to other building types.

Figure 1.2 illustrates the general methodology to address these objectives. The core issue of this research is to improve the two-way human-building interaction in indoor environment, i.e. to more accurately and objectively quantify the impacts of indoor environment on occupants and feedback such impacts to the building. The potential ways to achieve these are through subjective indicators, task-based indicators and physiological indicators. The correlations among the three indicators will also be explored, which can help to further strengthen the reliability of these indicators. On the whole building scale, the wellbeing and work productivity as represented by the three indicators and the corresponding measures to achieve better

wellbeing and work productivity will be evaluated through the building LCA platform, which can further guide a more balanced building design and operation.

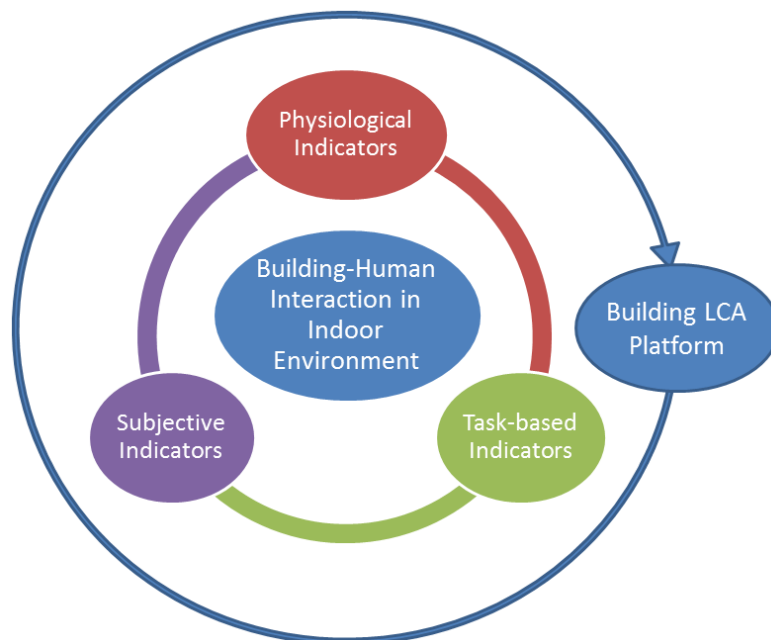


Figure 1.2 Research methodologies

1.3. Research roadmap and thesis layout

The detailed research roadmap according to the above research methodologies is shown in Figure 1.3. The solid lines/arrows define the scope of this research, and dashed arrows refer to the potential future works. In general, the impacts of indoor environment on wellbeing and work performance of occupants are experimentally investigated through subjective indicators, task-based indicators, and physiological indicators. The correlations among the three indicators are also be explored, and the physiological indicator is used as the major feedback mechanism. Outputs from these indicators are evaluated through life cycle platform.

- The indoor environmental quality aspects investigated in this study are indoor thermal environment and indoor air quality.
- Subjective questionnaires are used as subjective indicators. Behavioral tasks are

used as task-based indicators. Electroencephalogram (EEG) is used as physiological indicator. The impacts of IEQ on these indicators are studied, and the correlations among these three indicators are explored. Furthermore, in this research the EEG is studied as the major feedback mechanism to improve the building-human interaction. Machine learning-based EEG pattern recognition was explored as a potential feedback mechanism. The research scope for EEG-based methods to improve the building-human interaction is further illustrated in Figure 1.4. The solid lines define the scope of this research, and dashed arrows refer to the potential future works.

- LCC method is used as a starting point to incorporate the wellbeing and work performance into the building life cycle platform, as monetization is easier for comparison purpose. In this study the wellbeing represented by subjective indicators and the work performance represented by task-based indicators are used as inputs into the LCC framework.
- For the potential future works, one direction is to further explore the integration of EEG information into building control system, which then controls the indoor air quality based on EEG information and other inputs (such as environmental sensors' data). The impacts of IEQ on physiological indicator can also be used as inputs into the life cycle platform. Furthermore, physiological indicator as a feedback mechanism can also be evaluated through the life cycle platform, since feedback mechanism also requires energy and resources during the building operation. Finally, LCC is only a starting point, as broader metrics not limited to monetary values could also be used as inputs into the whole building LCA platform.

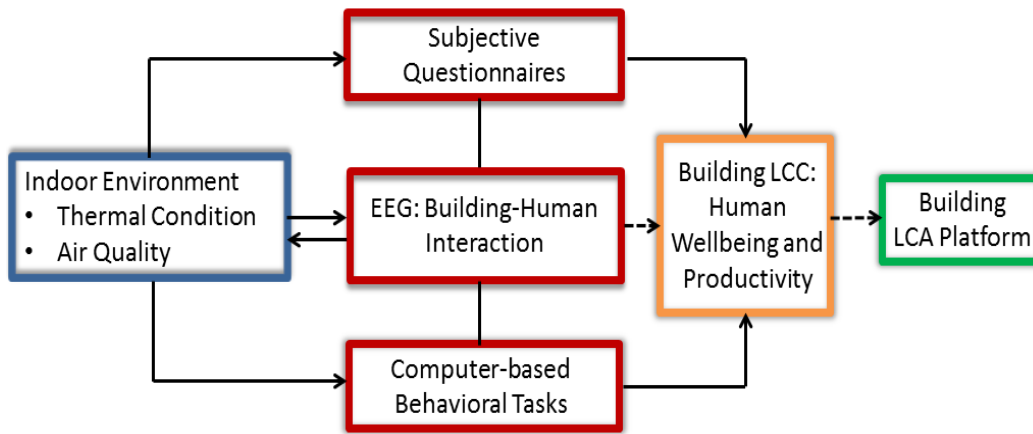


Figure 1.3 Research roadmap

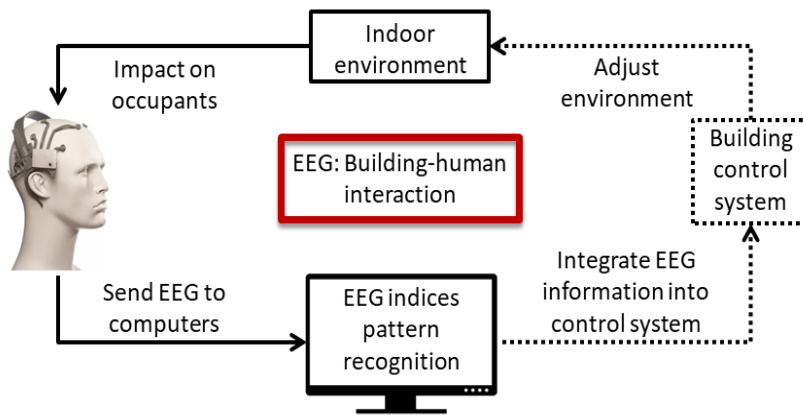


Figure 1.4 Research scope of EEG-based methods as the feedback mechanism in building-human interaction

The thesis layout according to the research roadmap is as follow:

- Chapter 2. Literatures of the relevant and state-of-the-art topics are reviewed. The topics include: impacts of indoor thermal environment and indoor air quality on human; current questionnaire-based methods, task-based methods and physiology-based methods to evaluate these impacts; the physiology-based EEG method in emotion and mental workload studies and their potential application for this research; machine learning based EEG methods; general human-building interaction studies; studies that evaluate the impacts of indoor environment on wellbeing and work performance

through life cycle platform.

- Chapter 3. This chapter is a preliminary experimental study. Specifically, this preliminary study compares students' thermal comfort, sick building syndromes and short-term performance under mixing and displacement ventilations in tutorial rooms. The main indoor environments studied are indoor thermal environment and indoor air quality.
- Chapter 4. This chapter evaluates the impacts of indoor environment on occupants through the LCC platform for educational buildings. A case study is conducted based on the experimental results from Chapter 3. Specifically, the monetized metrics are the benefit of avoided sick leave days for the wellbeing and the benefit of weighted average marks for the performance. These metrics are compared with other monetized values of building facilities and operational energy through the building life cycle.
- Chapter 5. This chapter studies the human-building interaction in indoor thermal environment using EEG methods. An experimental study investigating the impacts of various indoor temperatures on human subjects is conducted. Impacts of temperatures on subjective perception, work performance and EEG are studied. Correlations between EEG and subjective perceptions, and between EEG and tasks performance are also established. One machine learning based EEG pattern recognition method is also demonstrated.
- Chapter 6. This chapter focuses on the machine learning based EEG pattern recognition methods, which also form the main feedback mechanism. The data used to test the methods are from Chapter 5. Specifically, the linear continuous features of mental states under various temperatures are found and checked by interpolation and extrapolation. The performance of classifying different mental states under various temperatures is also compared among various machine learning methods.

- Chapter 7. This chapter studies the human-building interaction in different indoor air quality environments using EEG methods. An experimental study investigating the impacts of various indoor ventilation rates on human subjects is conducted. Impacts of indoor air quality on subjective perception, work performance and EEG are studied. Correlations between EEG and subjective perceptions, and between EEG and tasks performance are also established. Two machine learning based EEG pattern recognition methods are also demonstrated.
- Chapter 8. This chapter concludes the current study, and outlines potential future works.

Chapter 2 Literature review

2.1. Overview

In this chapter, literatures of the relevant and state-of-the-art research topics are reviewed. Impact of indoor environment on occupants' wellbeing and work performance are reviewed in Section 2.2. Previous evaluation methods of occupants' wellbeing and work performance are reviewed in Section 2.3. Potential EEG-based machine learning methods are reviewed in Section 2.4. General human-building interaction is reviewed in Section 2.5. Evaluation of occupants' wellbeing and work performance through the building life cycle platform is reviewed in Section 2.6. Finally, research gaps are elaborated in Section 2.7.

2.2. Impact of indoor environment on wellbeing and work performance

2.2.1. Temperature

ASHRAE standard 55 specifies thermally comfortable indoor environment by taking into account the combined effects of temperature, humidity, air speed and human factors (ASHRAE Standard 55, 2013). Among these indices, temperature is a crucial factor. The impact of temperature on thermal comfort is quite clear as suggested by the standard: i.e. either too high or too low will lead to thermal discomfort. However, the exact thresholds still depends on the situation. The suggested thresholds in the standard are mainly derived from studies in Europe or North America, which may not be suitable to be applied to other places. Furthermore, some studies found from the ASHRAE data base that within certain temperature thresholds the acceptability of thermal comfort was indistinguishable and therefore a particular "optimum" temperature was unnecessary (Zhang et al. 2011), as in contrast with the continuous approach adopted by the standard.

Apart from thermal comfort, the impacts of temperature on other subjective perceptions have also been studied. This generally includes perceived air quality, sick building syndromes (SBS) and perceived work performance. The SBS is widely and loosely defined by many, but in general, it is understood as a group of symptoms related but not limited to the irritation of the eyes, nose, throat, skin, breath, and other general symptoms such as headache and lethargy that temporally occur among occupants of a certain building but often disappear once occupants leave the building (Burge 2004). For instance, perceived air quality could deteriorate in warm environment when the temperature was higher and out of thermal comfort zone (Zhang et al. 2011). Findings from US EPA BASE study further suggested that higher temperatures even within the recommended thermal comfort range could still lead to higher prevalence of symptoms (Mendell and Mirer 2009).

For the impacts of temperature on work performance, the general view is that either being too cold or too warm can lead to decrease in performance for a wide range of cognitive-related tasks as suggested by a meta-analytic review study (Pilcher et al. 2002). Another literature review study by Seppanen et al. (2005) also summarized that the task performance decrements (0-16%) as a U-shape function of temperature (15-35°C). Studies in call centers (Niemelä et al. 2002) or laboratory (Lan et al. 2011) also showed that worker's performance began to drop with elevated temperatures (above 20°C). Wyon summarized from experimental results that work performance would drop when the temperatures were higher than neutral temperature (Wyon 1996), and Sundstrom also suggested that work performance would drop when human were under long-term warm condition (Sundstrom 1986). Wyon and Wargocki tried to explore the mechanisms behind the above phenomena: first, under moderate heat, sick building syndrome can be aggravated, and second,

in order to avoid perspiration, human's metabolic rate will decrease which can lower the arousal level (Wyon and Wargocki 2005).

On the other hand, some studies showed that temperatures slightly lower than neutral can improve work performance. A study in a call center in Singapore found that lowered temperature can lead to increased work performance (Tham 2004). Tham and Willem (2010) further explored the mechanisms behind, and showed that cooler environment can raise the arousal level and under moderate cold exposure induced nervous system activation was found, which was indicated by the increase of α -Amylase level and the Tsai-partington test.

2.2.2. Air movement

Apart from temperature, air movement is another major factor that contributes to thermal comfort according to ASHRAE standard, and the upper limit of air movement speed is prescribed for the centrally controlled ventilation. A review study showed that the perception of draft depended on many factors including air velocity, temperature, and personal factors (e.g. overall thermal sensation and activity level) (Toftum 2004). The sources of draft were often from leaky windows and open doors, or cooling devices where the outlets were installed on the ceiling (Griefahn et al. 2002). Draft could be desirable when the average temperature was quite high, as Xia et al. (2000) showed that within the range of 26°C to 30.5°C, thermal comfort could be achieved by higher draft velocity. Discomfort would also be induced if the speed was too high (Xia et al. 2000). Draft can also be satisfying if it is under individual control, i.e. personal ventilation. In many indoor cases, however, draft was not desirable when the thermal sensation is neutral or cooler (Toftum 2004). Various experiments showed that the main reason is that people are more sensitive to draft when they feel cold and under low activity level, which is common in the office building (Toftum and Nielsen 1996; Griefahn et al. 2001).

Again, the requirements on draft in current standards are mainly derived from people in Europe or North America, which may not be suitable for people in other places. Experiments regarding acceptable air speed range in Singapore were conducted for tropical people who had been passively acclimatized to hot conditions, and the preferred velocity range was found to be higher than the maximum velocity required under ASHRAE Standard 55 (Gong et al. 2006).

2.2.3. Relative humidity (RH)

Higher relative humidity can cause thermal discomfort as suggested by ASHRAE standard. Various studies have also investigated the impacts of relative humidity on human comfort. Tsutsumi et al. (2007) found positive effects of lower humidity on subjective perception under transient condition (from 30°C to 25.2°C) due to more evaporation from human body, but no significant difference in thermal sensation and humidity sensation among the 4 relative humidity (30, 40, 50 and 70%) levels when the temperature was fixed at 25.2°C. Another study also found that higher humidity at higher temperature level could lead to significant decrement in acceptability (Fang et al. 1998). Toftum et al. (1998) suggested the mechanism that higher humidity could lead to insufficient evaporative and convective cooling of the mucous membranes in the upper respiratory tract, and this in turn could lead to local warm discomfort and a perception of poor air quality. On the other hand, Wyon et al. (2006) found that subjective discomfort was present when the RH was lowered from 35% to 5%, though the effect was small even at 5% RH.

2.2.4. Indoor air quality (IAQ)

Indoor air quality (IAQ) in buildings can be improved by higher outdoor air supply rates, which removes bio-effluents and other indoor air pollutants such as particular matters and volatile organic compounds (VOC). For the outdoor air supply rates, ASHRAE Standard 62.1: Ventilation for Acceptable Indoor Air Quality (ASHRAE

Standard 62.1-2010) has recommended thresholds for different building types. For instance, the recommended minimum value is 2.5 L/s-person for office environment and 3.8 L/s-person for the classroom environment. Better IAQ can also be achieved by removing potential pollutants sources, such as furniture or old carpets.

The impacts of outdoor air supply rates on subjective perception have been studied extensively. A literature review suggested that ventilation rate under 10L/s-person could lead to the deteriorated perceived air quality and increased sick building syndromes (SBS) (Seppanen et al. 1999). This review study also suggested that the SBS would decrease significantly when the CO₂ concentration went below 800 ppm. A chamber study showed that the SBS would reduce when the ventilation rate increased from 3 to 10 L/s-person, with the CO₂ concentrations of 1690 and 900 ppm, respectively (Wargocki et al. 2000). Other field studies in call centers also showed that the reduction of SBS including intensity of dryness, aching eyes and nose-related symptoms might be correlated with the increase of outdoor air supply rate from 5 to 10 L/s-person (Tham 2004) . Another literature review further suggested that the SBS and short-term sick leave could reduce when the outdoor air supply rate increased up to 25L/s-person (Wargocki et al. 2002).

The impacts of outdoor air supply rates on work performance were also studied. Studies found that the task completion speed could increase in call centers (Tham 2004; Wargocki et al. 2004) with higher ventilation rates (5 to 10 L/s-person, with CO₂ concentration around 1226 to 805 ppm; 2.5 to 25 L/s-person, with CO₂ concentration around 1131 to 631ppm), or in school (Wargocki & Wyon 2007) with higher ventilation rate (3 to 8.5L/s-person, with CO₂ concentration around 1300 to 900ppm). In another call center the talking speed and post-talk wrap-up time to process information were also improved, though the benefits were small (Federspiel et al. 2004). Wyon (2004) also summarized from studies that the simulated works

performance could increase by increasing the outdoor air supply rates from 3 to 10 to 30 L/s-person.

In addition to the impacts of outdoor air supply rates, Wyon (2004) further summarized that the simulated works performance could also significantly increase by removing the common indoor sources of air pollution such as floor covering, personal computer and used supply air filter. For instance, laboratory experiments in Denmark and Sweden showed that by introducing an old carpet as a pollutant source, human subjects' perceived air quality decreased, sick building syndrome increased, and typing performance decreased (Wargocki et al. 1999, Wargocki et al. 2002). In addition, the impact of CO₂ has also been studied. Large scale data collected from 409 traditional and 25 portable classrooms from 22 schools were analyzed, and it was found through multivariate modelling that students' absence were significantly associated with indoor CO₂ concentration (Shendell et al. 2004). Similar findings were also derived from large dataset of company employees' sick leave and complaints of sick building syndrome (Milton et al. 2000; Erdmann and Apte 2004). Other study also showed that high CO₂ concentration level alone has negative influence on work performance. By keeping the ventilation rate constant and only varying CO₂ concentration (at 600, 1000, 2500 ppm), Satish et al. found that CO₂ concentration at 2500 ppm, which is within ranges found in common buildings, could lead to decrease in decision making performance (Satish et al. 2012).

2.2.5. Air conditioning and mechanical ventilation (ACMV) systems

Air conditioning and mechanical ventilation systems are widely used to control the indoor environment. One widely used system is mixing ventilation (MV), which supplies fresh air from ceiling level with high velocity to achieve an even distribution of temperature and pollutant in the whole space. Total mixing may not

be the most effective in many aspects, e.g. heat removal or pollutant removal (Cao et al. 2014), and high air velocity in MV can also lead to draft discomfort in workplaces (Griefahn et al. 2002). Compared with MV, displacement ventilation (DV) method has been proposed to supply fresh air near floor level on the side wall and return exhausted air near ceiling level by buoyant force, as fresh air is warmed up by heat sources in the room. DV was originally proposed to save energy and improve IAQ in the breathing zone. However, several studies revealed that DV can improve IAQ in the breathing zone if heat sources produce the contaminants, but may decrease IAQ if the contaminants are from the floor covering or other unheated sources (Melikov et al. 2005). DV can also lead to draft discomfort around feet and excessive air stratification (ASHRAE Standard 55, 2013).

Most studies that compared IAQ and thermal comfort between MV and DV were conducted in environmental chambers. Experimental studies compared human subjects' thermal sensation in environmental chamber and found that thermal neutral temperature in DV was slightly higher than that in MV (Fong et al. 2011; Fong et al. 2015). Another chamber measurement in Denmark revealed that the vertical distributions of air temperature and velocity were more uniform in MV than those in DV, and local turbulence intensities at neck level were larger in MV than those in DV (Wu et al. 2015). A further chamber study which involved human subjects and compared different ventilation strategies including MV and DV suggested that operative temperature alone was not sufficient for the prediction of thermal sensation under non-uniform conditions (Schellen et al. 2013).

On the other hand, limited studies have compared occupants' responses to MV and DV in the field. Two studies compared pupils' perceived IAQ and SBS in elementary classrooms (all with heating mode) in Sweden. Smedje et al. found that environmental parameters (temperature and concentration of CO₂) were similar in

each ventilation mode at breathing height, and children's perceived IAQ were similar in the two ventilation modes, except that DV had more reported eye symptoms (Smedje et al. 2011). Norbäck et al. found that temperature at desk level and many pollutants' concentration (CO₂ and formaldehyde) were numerically elevated in MV, and DV may have certain positive health effects among pupils (Norbäck et al. 2011).

2.3. Previous evaluation methods of wellbeing and work performance

2.3.1. Questionnaire-based and task-based methods

Evaluation of subjective wellbeing mainly uses questionnaires. For instance, ASHRAE standard 55 provides sample questionnaires that can be used for thermal comfort evaluation. For other types of subjective feelings such as perceived air quality and sick building syndromes, different researchers have adopted different questions according to their research purposes, and representative questions can be found in the following studies: Fanger et al. 1988, Raw et al. 1996, Wargocki et al. 1999, Gong et al. 2006, and Melikov et al. 2013. In these questionnaires aspects of indoor environment and subjective perceptions were rated on continuous or discrete scales.

Evaluation of work performance can be roughly divided into two categories. The first category is field intervention and observation, such as the call centers studies as reviewed in Section 2.2.4. In this type of study however, there might be many other unknown confounding factors, and the results are also difficult to be applied to other situations. The second category is laboratory based studies, where environmental conditions can be more accurately controlled. In this type of study, human subjects are often recruited and required to complete certain tasks, from simple tasks such as typing or proof-reading (Wargocki et al. 2000, Wargocki et al.

2002), to more complicated tasks such as cognitive (Lezak et al. 2004; Solso et al. 2007) or decision making tasks (Satish et al. 2012).

2.3.2. General physiological methods

General physiological indices have also been utilized to quantify the impacts on occupants. These indices were also used to correlate with questionnaire-based and task-based methods. These indices include skin temperature, heart rate, respiration ventilation, blink rate, end-tidal partial CO₂ (ETCO₂), arterial blood oxygen saturation (SPO₂), biomarkers in saliva and tear film quality, functional magnetic resonance imaging (fMRI) (Lan et al. 2011; Tham et al. 2010; Hocking et al. 2001; Kanosue et al. 2002). Following is a brief explanation for some of these methods.

- Heart rate (HR) and heart rate variability (HRV). Heart rate is the number of heart beat per minute, and heart rate variability refers to the beat-to-beat alterations in heart rate. Under rest conditions, the Electrocardiograph (ECG) of healthy individuals exhibits periodic variation in R-R interval. R-R interval refers to the time duration between two consecutive R waves of ECG. The perturbation of these R-R intervals is usually used to study the Autonomic Nervous System (ANS) activity. Yao et al. have shown that this index may be a potential index to study the impact of indoor environment on ANS activity (Yao et al. 2009). HRV has also been used to study cognitive functions and effects of physical effort (Luft et al. 2009).
- End-tidal partial CO₂ (ETCO₂). The concentration of end-tidal partial CO₂ is the partial pressure of carbon dioxide at the end of an expiration, which is usually used to approximate arterial CO₂ non-invasively (Wientjes et al. 1998). Some research has shown that under warm condition (30°C), higher ETCO₂ was observed as a result of higher metabolic rate, which resulted in more CO₂ production inside the human body (Lan et al. 2011).

- Peripheral capillary oxygen saturation (SPO₂). SPO₂ measures the oxygen saturation level in the blood, which can be accomplished with a non-intrusive pulse oximeter device. Many medical studies have shown that people generally feel more tired and show a decrease in mental performance when the concentration of oxygen saturation level is low (Noble et al. 1993, Chung et al. 2004, Sung et al. 2005). Some research has shown that under warm condition (30°C), SPO₂ decreased significantly, which is also due to higher metabolic rate and more oxygen consumption inside the human body (Lan et al. 2011).
- Functional magnetic resonance imaging (fMRI). This method has also been used to study brain activities for thermal comfort (Hocking et al. 2001; Kanosue et al. 2002). This is a neuroimaging technique that detects the changes associated with blood flow in the brain, as cerebral blood flow is coupled with brain activity.

2.3.3. EEG-based physiological methods

Another simpler, non-intrusive method is electroencephalography (EEG), which records activity of the brain by measuring electrical signals on the surface of scalp. Some previous studies have utilized this method to investigate the impacts of indoor environment on human. Deboer (2002) showed that frequencies in the EEG change in parallel with changes in body or brain temperature. Yao et al. (2008) and Lan et al. (2010) used bipolar method (one on the right side of the head, another at the center of the forehead, and a third on the earlobe as reference) to investigate impacts of indoor temperature on EEG signal, and concluded that the power of various EEG frequency ranges were different under various temperatures. Choi et al. (2015) used 8 channels EEG headset to monitor brain activities under various combined indoor environment, and concluded that high-beta wave in the temporal lobe can be used to assess the stress.

In the EEG study domain, the brain activities can be quantified by the power densities of different frequency ranges, which have been extensively studied in the past century. There are five major brain waves with different frequency ranges (Sanei and Chambers 2007). In general, Delta wave is within the range of 0.5-4 Hz, which is primarily associated with deep sleep. Theta wave is within the range of 4-8 Hz, which is regarded as consciousness slips towards drowsiness. Alpha wave is within the range of 8-13 Hz, and is the most prominent rhythm in the whole realm of brain activity. Alpha wave is often present in relaxed awareness without attention or concentration, and reduces or disappears by hearing unfamiliar sounds, or by mental concentration or attention. Beta wave is within the range of 13-30Hz (though in some literature no upper bound is given), which is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world or solving concrete problems. The amplitude of beta is smaller compared with previous three bands. The frequencies above 30 Hz (mainly up to 45 Hz) correspond to the gamma range, and the amplitude of gamma wave is often much smaller.

2.4. EEG-based machine learning methods

A potential way to improve human-building interaction in the indoor environment is to utilize machine learning-based EEG pattern recognition methods, which are widely studied human-computer interaction techniques in EEG emotion research (Esfahani et al. 2011; Frantzidis et al. 2010; Picard et al. 2001) and EEG mental workload/vigilance research (Gevins et al. 1998; Berka et al. 2004). Typical machine learning methods are statistics-based methods or more advanced neural network-based methods (Matlab R2013b). The essential idea of machine learning is to train a computer classifier with known data (i.e. the specific classes of different training data are already known), and this classifier will then be used to classify unknown data according to certain methods (i.e. to predict the classes that the

unknown data belong to). Classes are often pre-defined in a particular field, such as different classes of emotions in the emotion field, or different classes/levels of mental workloads in the workload field. These machine learning-based EEG methods in the human-computer interaction domain have the potential as the medium for the future human-building interaction, especially as a new feedback mechanism to the building. In this interaction, different mental states caused by different indoor environments can be monitored and classified in real-time through EEG, and the classification results can be used as the wellbeing and performance indicators to feedback to the building control.

For the machine learning-based EEG emotion studies, the two dimensional Arousal-Valence model (Russell 1979) is commonly used, where arousal denotes the intensity of emotion and valence denotes the positive/negative characteristics of emotion. Different emotions can be elicited through the International Affective Picture System (IAPS) (Lang et al., 2005) or the International Affective Digitized Sounds (Bradley et al. 2007), and these databases map different sounds or pictures that denote different classes of emotion onto the 2D Arousal-Valence space. The transition among emotions is assumed as continuous, and these databases have large amount of classes that cover the 2D space. In machine learning-based EEG emotion studies (Sourina et al. 2011; Frantzidis et al. 2010), human subjects were exposed to these sound or picture databases while their EEG signals were recorded, and the recorded EEG signals were then used to train and classify mental states of different emotions. Typical classes of different emotions are low-arousal-positive-valence class (e.g. calm), high-arousal-negative-valence class (e.g. angry), or other pre-defined narrower classes. For the machine learning-based EEG mental workload/vigilance research, the basic idea is similar. Different levels of workload (Gevins et al. 1998) or vigilance (Berka et al. 2004) were elicited by mental tasks of different difficulties. In these studies the number of levels/classes was often small

(e.g. only had high, intermediate and low levels), and the mental states were also implicitly assumed as continuous. However, this limited amount of established levels/classes might pose problems for future application when more precise levels within or beyond these established levels are required.

Representative machine learning algorithms in these studies are illustrated below. The illustration is based on the Matlab documentation (Matlab R2013b), and all these algorithms have relatively fast training and prediction speed.

a) LDA classifier. The LDA classifier models each class as a multivariate normal distribution, and assigns the same covariance matrix to each class. Each observation is expressed as a vector, and all observations are of the same dimension d , meaning that the number of features is d . The data for training is a set of observations with known classes. To train a LDA classifier, for each class the parameters of a multivariate normal distribution were estimated with training data. To classify the unknown observations, the trained LDA classifier seeks to minimize the expected classification cost in Eqn 2.1.

$$\hat{y} = \arg \min_{y=1,\dots,K} \sum_{k=1}^K \hat{P}(k|x)C(y|k) \quad (2.1)$$

where \hat{y} is the predicted classification; K is the number of classes; $\hat{P}(k|x)$ is the posterior probability of class k for observation x ; and $C(y|k)$ is the cost of classifying an observation as y when its true class is k . In this study, the default values for cost function were used, namely $C(y|k)=1$ if $y \neq k$, and $C(y|k)=0$ if $y=k$. In other words, the cost is 1 for incorrect classification, and 0 for correct classification.

The posterior probability $\hat{P}(k|x)$ that an observation x is of class k is defined in Eqn 2.2.

$$\hat{P}(k|x) = \frac{P(x|k)P(k)}{P(x)} \quad (2.2)$$

where $P(k)$ is the prior probability of class k , which is empirically defined as the number of training samples of class k divided by the total number of training samples in this study; $P(x)$ is a normalization constant, namely, the sum over k of $P(x|k)P(k)$; and $P(x|k)$ is the multivariate normal density defined in Eqn 2.3.

$$P(x|k) = \frac{1}{(2\pi|\Sigma_k|)^{1/2}} \exp \left\{ -\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) \right\} \quad (2.3)$$

where μ_k is the mean; Σ_k is the covariance matrix; $|\Sigma_k|$ is the determinant; and Σ_k^{-1} is the inverse matrix.

The LDA is normally accurate when the assumptions are met, i.e. each class is multivariate normally distributed. Otherwise the prediction accuracy will vary. The computing memory usage is relatively low.

b) SVM classifier. The SVM classifier can only handle two classes. The SVM classifies data by finding the best hyper-plane (decision plane) that separates data points of one class from those of the other class. The best hyper-plane for an SVM means the one with the largest margin between the two classes, and the margin means the maximal width of the ‘slab’ parallel to the hyper-plane that has no interior data points. The support vectors are the data points that are closest to the separating hyper-plane; these points are on the boundary of the ‘slab’.

The data for training is a set of vectors x_I along with their known classes y_I . For some dimension d , the $x_I \in R^d$, and the $y_I = \pm 1$. The equation of a hyper-plane is defined in Eqn 2.4.

$$w^T x + b = 0 \quad (2.4)$$

The best separating hyper-plane is defined by w and b that minimize $\|w\|$, subject to the constraint $y_I(w^T x_I + b) \geq 1$. The unknown data z is then classified according to $\text{class}(z) = \text{sign}(w^T z + b)$.

The above minimization problem is often solved by the equivalent dual quadratic programming problem. To obtain the dual, take positive Lagrange multipliers α_I multiplied by each constraint, and subtract from the objective function, which gives Eqn 2.5:

$$L_p = \frac{1}{2}(w^T w) - \sum_i \alpha_i (y_i(w^T x_i + b) - 1) \quad (2.5)$$

Setting the gradient of L_p to 0 gives Eqns 2.6:

$$w = \sum_i \alpha_i y_i x_i; \quad 0 = \sum_i \alpha_i y_i \quad (2.6)$$

Substituting Eqns 2.6 into Eqn 2.5, the dual L_D is given in Eqn 2.7:

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j (x_i^T x_j) \quad (2.7)$$

L_D was then maximized over $\alpha_I \geq 0$. In general, many α_I are 0 at the maximum. The nonzero α_I in the solution to the dual problem define the hyper-plane as shown in Eqns 2.6. The data points x_I corresponding to nonzero α_I are the support vectors. The derivative of L_D with respect to a nonzero α_I is 0 at an optimum, which gives $y_I(w^T x_I + b) - 1 = 0$. This can give the value of b , by taking any I with nonzero α_I .

In case that a separating hyper-plane cannot be found (i.e. non-separable data), SVM can use a soft margin, meaning a hyper-plane that separates many but not all

data points. The default sequential minimal optimization (SMO) for SVM in Matlab that solves L^1 -norm problem was used in this study in case a soft margin is needed. The L^1 -norm problem is given in Eqn. 2.8:

$$\min_{w,b,s} \left(\frac{1}{2} (w^T w) + C \sum_i s_i \right) \quad (2.8)$$

subject to the constraint $y_i(w^T x_i + b) \geq 1 - s_i$ and $s_i \geq 0$. C is a non-negative cost parameter that places weight on the slack variables s_i , meaning the optimization attempts to make a stricter separation between classes. The corresponding dual problem formulation for soft margin is similar to the previous discussion.

c) Naive Bayes classifier. The NB classifier can be used when features are independent of one another within each class, but it often works well in practice even when the independent assumption is not valid. To train a NB classifier, the method estimates the parameters of a probability distribution, assuming features are conditionally independent given the class. To classify the unknown data, the method computes the posterior probability belonging to each class. The method then classifies the test sample according to the largest posterior probability. The class-conditional independence assumption greatly simplifies the training step, as one-dimensional class-conditional density for each feature can be estimated individually. Normal density distribution was used in this study, i.e. each feature is modeled with a normal distribution, and the classifier estimates a separate normal distribution for each class by computing the mean and standard deviation of the training data in that class. Other parameters in the NB classifier were kept default. The prediction accuracy is medium. The computing memory usage for normal distribution modeling is low.

d) K-nearest neighbor classifier. This method categorizes the unknown data based on their distance to points in the training dataset, which can be simple yet still effective. Using a rule based on the majority vote of the k-nearest neighbors' classes, the unknown data can be classified accordingly. Many different types of distance metrics are available, and the Euclidean distance was used in this study. Other parameters in the KNN classifier were kept default. Given m_x (1-by- n) vectors x_1, x_2, \dots, x_{m_x} and m_y (1-by- n) observation vectors y_1, y_2, \dots, y_{m_y} , the Euclidean distance between the vector x_s and y_t is defined in Eqn 2.9.

$$\text{Euclidean distance: } d_{st}^2 = (x_s - y_t)(x_s - y_t)' \quad (2.9)$$

The prediction accuracy is often good in low dimensions, but may be poor in high dimensions. The computing memory usage is relatively high.

2.5. General human-building interaction

Human-building interaction is a subject not limited to the indoor environmental quality. One category of methods that tries to improve this interaction focuses on understanding human behaviors in buildings through psychology and sociology methods. For instance, some researcher put forward a psychological framework to predict human behaviors in buildings that can help to achieve a better energy-relevant interaction with buildings (von Grabe 2016). Other researchers also adopted psychosocial methods to examine the interaction of built environment and human physical activity such as leisure walking (Ding et al. 2012). Another literature review examined psychosocial studies that investigated the impacts of various built environment components on human, including windows, lights, blinds, air-conditioning, thermostat, fans and doors patterns (Stazi et al. 2017). On the other hand, information technology based methods have also been utilized. For instance, some researchers tried to develop an automatic stress detection method in working

environments by using smartphone's accelerometer data (Garcia-Ceja et al. 2015). Dalton et al. (2016) further elaborated that the methods in the human-computer interaction domain should be incorporated into the built environment.

For the indoor environmental quality in particular, both the psychosocial methods and information technology methods have been studied for the human-building interaction. For instance, some researchers developed and validated an agent-based model of occupant behavior using data from a one-year field study in a medium-sized, air-conditioned office building and Perceptual Control Theory (Langevin et al. 2015). The same group of researchers also combined predicted human behaviors with EnergyPlus simulation model to develop a Human and Building Interaction Toolkit (Langevin et al. 2016). Jazizadeh et al. (2014) proposed a framework to integrate occupants' personalized thermal comfort votes into the air conditioning system control loop. Another human-building interaction study tried to incorporate Computational Fluid Dynamics (CFD) data into the augmented reality (AR) (Malkawi et al. 2005).

2.6. Building lifecycle assessment platform

Various sustainability assessment tools have been developed and widely used, and one of them is life cycle assessment (LCA). LCA is an approach to analyze the environmental impact of products or activities throughout the life cycle stages (ISO14044: 2006). Derived from LCA, a parallel framework can be established to make different metrics in LCA comparable in the form of life cycle costing (LCC), which monetizes metrics in LCA over the lifetime and discounted to current values (Hoogmartens et al. 2014). For buildings, the CEN/TC 350-sustainability of construction works (European Committee for Standardization) recommends consideration of four life cycle stages from product stage including raw materials supply, transport, and manufacturing; to construction stage including transport and

construction–installation on-site processes; to use stage including maintenance, repair and replacement, refurbishment, and operational energy use such as heating, cooling, and ventilation; and to end-of-life stage including deconstruction, transport, recycling/re-use and disposal (EN 15643-1:2010). Previous researchers have done extensive studies on LCA of different types of buildings in various locations. Ortiz et al. conducted a literature review on building LCA, including the whole building LCA and building materials and components LCA (Ortiz et al. 2009). Typical metrics in LCA studies are energy consumption, pollutant emissions, carbon footprint and other factors that have potential environmental impact. Building LCC has also been widely used to optimize different building parameters such as insulation thickness, building shape, and building retrofits, in order to minimize potential cost during the building lifespan. For LCA/LCC, owing to different objectives, the life cycle stages and impact assessment indicators that were taken into account varied from case to case, and some of the life cycle stages can be excluded provided there are supportive assumptions and reasons.

There are already quite many studies that have investigated human wellbeing and work productivity through the life cycle perspective, and these studies focused on the office buildings' indoor environment and the corresponding cost-benefit metrics in LCC framework. Better indoor environment in these studies often refers to condition that can provide better thermal comfort and indoor air quality (IAQ). Woods suggested that in office buildings, the salaries of workers exceeded the building energy and maintenance costs by approximately a factor of 100, and salaries exceeded annualized construction or rental costs by almost as much (Woods 1989). A detailed review study showed that the increased benefits from reduced health problems, sick building syndromes (SBS) and increased work performance due to better indoor environment far exceeded the increased building operational costs in office buildings in United States, and cited two examples of calculation

with benefit-cost ratios of 9 and 14 (Fisk 2000). Wargoeki et al. conducted a complete simulation study by using the relationship between office work performance and IAQ from previous studies, and increased performance due to better IAQ was converted into annual revenues using average worker salary in United States. The study concluded that for various scenarios, the annual increase in productivity was worth 6-115 times as much as the increase in annual energy and maintenance costs, and the LCC results showed that the discounted payback time for the additional capital cost of improving heating & ventilation and air conditioning (HVAC) were below 2.1 years (Wargoeki et al. 2005). Fisk et al. focused on the health and wellbeing by using the modelled relationship between IAQ and sick leave from previous studies, and they estimated that the economic benefit from reduced sick leave could also be significant (Fisk et al. 2005). Johansson conducted a more general simulation by incorporating costs of health, wellbeing and work productivity into the LCC study, using the modeled relationship between IAQ, sick leave and work performance from previous studies, and concluded that the benefit of human factors is clear and can be used to optimize the air supply rate in building design (Johansson 2009).

For other building types, especially educational buildings, studies of effects of indoor environment on human wellbeing and work productivity are relatively less. Two literature review studies (Wargoeki et al. 2013; Mendell et al. 2005) summarized results from various field interventions or experimental studies, attributing adverse health effects and reduced performance of students to poor indoor thermal or air quality conditions. On the other hand, study of these effects on students through the perspective of building LCC/LCA cannot be found. This lack of study may be mainly due to the fact that unlike office buildings, educational buildings are for non-profit purposes, which makes it more difficult to investigate through LCC perspective. However, such issues still need to be properly addressed.

Wargoeki et al. (2013) pointed out in the literature review that the thermal or air quality conditions in school classrooms are often worse than the relevant stipulations in standards and building codes, partly due to inadequate financial resources for maintenance and upgrade of school buildings. Without proper sustainability assessment tools like LCA/LCC, such issues may not be properly assessed and addressed in a more holistic way.

2.7. Knowledge gaps

A comprehensive summary of knowledge gaps based on the literature review is illustrated below. This is also a detailed elaboration of the main problems as stated in Chapter 1.2.

- The impacts of various indoor environmental quality indices on human's wellbeing are extensively studied and the general trends are clear, but the suggested thresholds are different and the mechanisms behind are not well understood.
- The impacts of various indoor environmental quality indices on human's work performance are also extensively studied, but the general trends are less clear and the suggested thresholds vary significantly among the studies. The mechanisms behind are not well understood either.
- Questionnaire-based evaluation methods are prone to perception biases. The results of task-based evaluation methods depend heavily on the types of tasks being used. Most of the previous physiology-based methods used in indoor environment studies are very cumbersome to implement and may not be sensitive and clear enough. Furthermore, the correlations of physiology-based methods with traditional questionnaire-based and task-based methods are also less studied.

- Previous EEG-based physiological methods use either very limited number of channels or very limited types of indices. Limited number of channels or indices may lead to incomplete information.
- EEG-based machine learning methods have the potential to be used in the indoor environment studies. However, the current studies that use EEG-based machine learning methods are in the emotion and mental workload research areas, and their applicability to the indoor environment needs to be examined. Furthermore, the limited amount of established levels/classes in these research areas might pose problems for future application when more precise levels within or beyond these established levels are required. For instance, if more precise identification of mental workload between the established high and intermediate levels is required, then the EEG data of this level of mental workload needs to be elicited and collected by additional experiments.
- General human-building interaction studies focus on the impacts of built environment on occupants, while the feedback mechanisms are seldom studied. This issue also applies to the studies for the human-building interaction in indoor environment. Furthermore, the main aspects considered in these studies are perceptions or behaviors of occupants, while their work productivity is often ignored.
- The building life cycles studies that take into account occupants' wellbeing and work performance had very different results, mainly because their inputs and methods were different. Furthermore, these studies focus on office building type only, and other building types are not considered.
- For ventilation systems that control indoor environment, most studies compare MV and DV systems in laboratory, but very few compare their field performance.

Chapter 3 Comparing mixing and displacement ventilation in tutorial rooms: students' thermal comfort, sick building syndromes, and short-term performance

3.1. Overview

This chapter is a preliminary study, and the main indoor environmental indices studied are indoor thermal environment and indoor air quality (IAQ). Specifically, a field experiment was conducted in two identical tutorial rooms to compare human subjects' thermal comfort, sick building syndromes (SBS), and short-term performance under MV and passive displacement ventilation (PDV). In addition, feedbacks from real-life occupants using tablet devices with simplified subjective questions further complemented the experiment.

3.2. Methodology

3.2.1. Experiment

The experiment was conducted in two side-by-side tutorial rooms on Nanyang Technological University, Singapore. Layout of the rooms is shown in Figure 3.1. The rooms are 8m in length, 8m in width, and 2.75m in height (floor to false ceiling). The two rooms are identical except for their ventilation systems. One tutorial room has traditional mixing ventilation with cooling coil, and the other room has displacement ventilation with cooling coil. Both rooms do not have exhausts, so the indoor air is driven out through natural leaking. In particular, the displacement ventilation used in the tutorial room is passive displacement ventilation (PDV). The PDV system employs the natural convection of heat transfer without mechanical fans to deliver the chilled air to the occupants. By taking advantage of the natural buoyancy of warm air in the room, chilled air produced by the cooling coil sinks to the floor and is driven by the temperature gradient. Stable stratification is achieved across the height of the room.

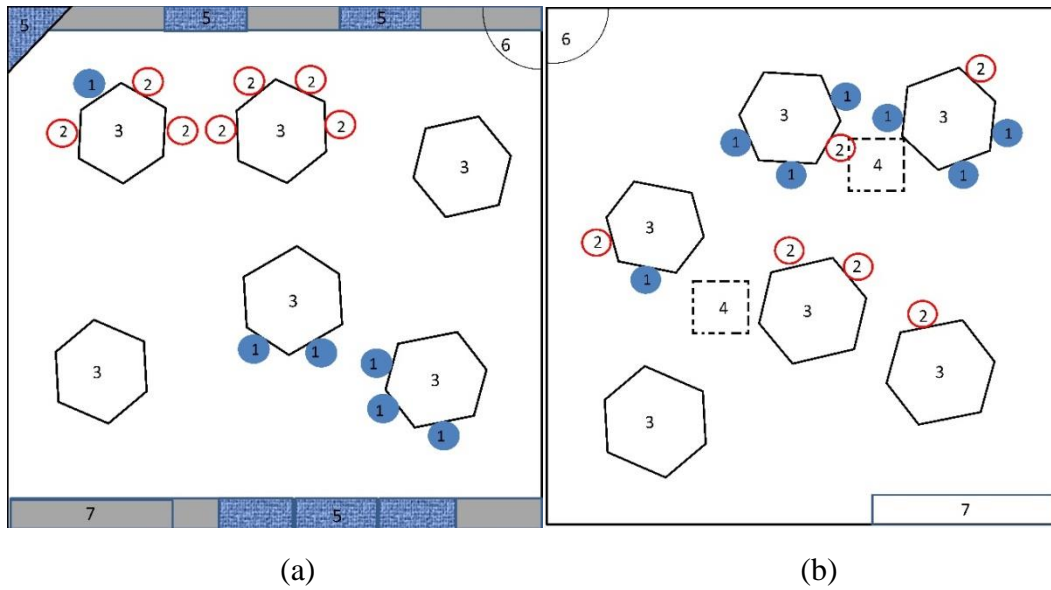


Figure 3.1 Layout of the tutorial rooms and occupied seats in the experiment: (a) MV room; (b) PDV room. 1= seats occupied by subjects that led to larger draft sensation or colder thermal sensation (solid circles); 2= seats occupied by subjects that led to smaller draft sensation or warmer thermal sensation (hollow circles); 3=tables; 4=overhead MV diffusers; 5=floor PDV diffusers; 6=doors; 7=computer control panels.

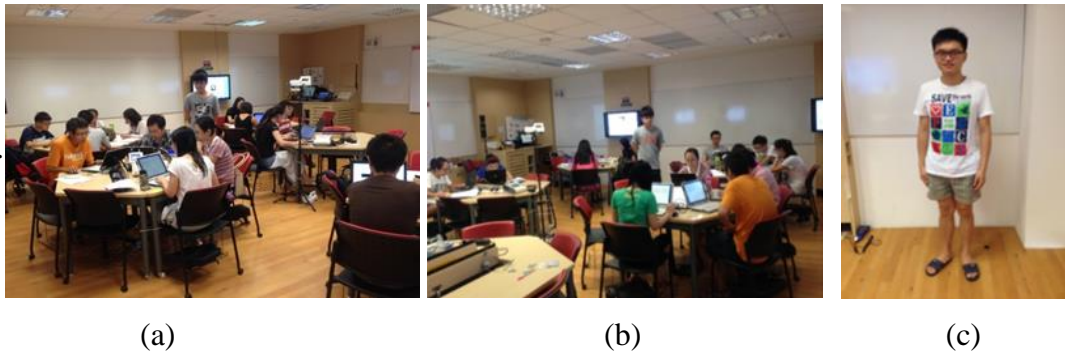


Figure 3.2 Site photos: (a) MV room; (b) PDV room; (c) Dressing code: short-sleeve shirt, shorts, and saddle without socks.

Thirty-nine healthy university students (male-female ratio was 6:7) were recruited as human subjects to participate the experiment and they were required to wear common attire of local students (short-sleeve shirt, shorts, and saddle without socks as shown in the Figure 3.2) in Singapore. This clothing level is 0.36clo according to the ASHRAE Standard 55. Before the experiment, they were asked to keep good

physical conditions. Seating was arranged to avoid positions close to doors or computer control panels.

Human subjects first participated in two consecutive non-working days, i.e. within-subject, in the MV room in day 1 and in the PDV room in day 2. Subjective questionnaires were designed to investigate thermal comfort and SBS. Computerized task-based tests were designed to evaluate performance, and measurements were taken to control for learning effect, including 1) tasks were chosen such that they require very basic abilities; 2) a practice session was conducted to help human subjects to be proficient with the tasks before the formal experiment, and 3) two parallel sets of questions with similar difficulty but different contents were used in formal experiment.

The experimental procedure in each session is shown in Figure 3.3. Thirty-nine human subjects formed three groups evenly to participate in three sessions in each day: one morning session from 9:30am to 11:30am, one afternoon session from 1:00pm to 3:00pm, and one afternoon session from 3:30pm to 5:30pm. To minimize other confounding factors, human subjects attended the same session in the same time slot in both days.



Figure 3.3 Procedure for each 120-minute session

Since concentration of many indoor air pollutants correlates to CO₂ concentration when building occupants are present, concentration of CO₂ was used as the indicator of IAQ in this experiment. During the first two-day experiment, CO₂ built-up was as high as 2600 ppm in the MV room due to poor ventilation design of the MV system while CO₂ concentration in the PDV room was normal (below 1000

ppm). The high CO₂ scenario was not part of the original experimental design. It happened due to the inadequate air exchange rate by the fan-coil unit (FCU) in the actual tutorial room. This also reflects the potential problems of FCU in many other indoor environments. To fix this problem, after the first two-day experiment an extra fan was installed in the MV room to draw in fresh air and to lower CO₂ concentration to below 1000 ppm, while the PDV room remained unchanged. The extra fan was installed at the duct located outside the room to increase the outdoor air intake, which increased the air exchange rate by around 1/hr. However, due to the high re-circulated air flow in the FCU, the extra outdoor air only increased the air flow velocity by around 0.1 m/sec at the diffuser exit on the ceiling. The associated impact on the air flow at 1.5m height is therefore negligible. Another two-day experiment was then conducted at the same sites one month later. Only 28 human subjects who participated in the 1st two-day experiment were able to join the 2nd two-day experiment. The 28 human subjects still attended in the same time slots and seated at the same locations as they did in the 1st two-day experiment, and 11 new human subjects with a male-to-female ratio of 4:7 had to be recruited.

Overall, four scenarios were: 1) MV I, high CO₂ concentration, day 1; 2) PDV I, normal CO₂ concentration, day 2; 3) PDV II, normal CO₂ concentration, day 3; and 4) MV II, normal CO₂ concentration, day 4. During the experiment, temperature set-point was 23°C which represented the normal setting in the tutorial rooms. CO₂, temperature and relative humidity (RH) were continuously monitored by CO₂ meters (model CM-0018, CO₂ Meter, Inc. USA). Air-velocities at outlets of diffusers in both rooms were recorded by air velocity meters (Velocicalc air velocity meter 9545, TSI Inc.). Sampling rate for all data points was at 5-second intervals, and then the data were processed to produce 2-min average intervals for data analysis purpose. The cooling load was mainly contributed by the laptops and human occupants. The chilled water consumption is recorded by the iSOLV BTU

Measurement System (model iSOLV BTU981-PT2, Flotech Inc., Singapore). An InfraRan Specific Vapor Analyzer (Wilkes Enterprise Inc., East Norwalk, USA) was used to measure the air-exchange rates (AERs). The AER was calculated through sulphur hexafluoride (SF₆) tracer decay method. The accuracy of CO₂ measurement was $\pm 30\text{ppm} \pm 3\%$ of measured value. The accuracy of air velocity measurement was $\pm 3\%$ of reading or ± 0.015 m/s, whichever was greater. The accuracy of temperature measurement was $\pm 0.3^\circ\text{C}$. The accuracy of relative humidity was $\pm 3\%$ RH. These small uncertainties were not expected to affect human responses. All instruments were calibrated before the experiment.

3.2.2. Real-life occupant feedback

The well-controlled experimental condition described above inevitably lacked certain aspects of real-life situation, e.g. occupants may spend different amount of time or conduct different types of tasks. The number of data point in experiment is also relatively smaller than that in real-life situation. Therefore, after the experiment, real-life occupant feedback was conducted for two months at the same sites to complement the experiment. The occupants who gave real-life feedback were students having tutorial in weekdays. A tablet device with touchscreen was installed in each tutorial room to invite occupants' feedback on similar subjective questions as those in the experiment. Both rooms remained in their initial condition, and the MV room had no extra fan. The temperature set-points of the two rooms were the same, while all other environmental parameters could not be continuously monitored. The clothing level in real-life feedback was impossible to control, but should range within 0.32-0.57 according to the observation.

3.2.3. Subjective questionnaire and computerized tasks

In the experiment, the questionnaire used to investigate subjective feeling of occupants towards the environment was compiled from ASHRAE Standard 55 and

other literatures (ASHRAE Standard 55, 2013; Fanger et al. 1998; Raw et al. 1996; Wargocki et al. 1999; Gong et al. 2006; Melikov et al. 2013). The questionnaire can be found in the Appendix B. The questionnaire used 7-point scale to rate different aspects of indoor environment (thermal and draft) and SBS. Instead of -3 to 3 scale for thermal and draft sensation, 1 to 7 scale was used in order to keep the same format with other physiological question scale, and therefore 4 represents the neutral state. In brief summary, (1) for draft sensation: 1 refers to more still, and 7 refers to more breezy; (2) for thermal sensation: 1 refers to cold, and 7 refers to hot; (3) for whole body draft acceptability, whole body thermal acceptability, and SBS: 1 refers to very unacceptable/very bad, and 7 refers to very acceptable/very good.

The work performance evaluation questions used in the experiment were compiled from cognitive psychology, behavioural psychology and neuropsychology. These tasks were developed into question sets (sample questions can be found in the Appendix C), and computerized for better implementation. Representative types that contain different aspects of mental activities are listed below. These tasks were commonly used in the previous environmental chamber studies, and were believed to represent essential aspects of mental activities.

- Short term memory: Two types of short term memory tests were selected. Pair recall asked human subjects to remember two groups of character pairs each time followed by recalling the missing character in each pair (Kantowitz et al. 2009). Words recall asked subjects to remember two groups of words each time followed by recalling the words in each group (Solso et al. 2008).
- Reaction time: This test asked human subjects to type the character shown on the screen as fast as possible to evaluate the reaction time (Lezak et al. 2004).

- Perception: Three types of perception tests were selected. Visual trace asked human subjects to visually trace each curve and correctly label it (Yin 2003). Shape identification asked human subjects to find out the designated shapes from a large pool of similar shapes (Yin 2003). Stroop test asked human subjects to judge whether the meaning of the words correspond to their actual color as shown (Solso et al. 2008).
- Mental arithmetic: This test asked human subjects to compute 2-digit by 2-digit multiplications to evaluate mental arithmetic. The results of multiplications were all 3 digits (Wetherell 1996).

For the real-life occupant feedback, a lengthy subjective questionnaire was impractical as that in the experiment. Therefore only five representative questions were used in the real-life feedback: thermal sensation, draft sensation, perceived IAQ, perceived health, and perceived work performance. The first four questions investigated thermal comfort and SBS, and the final question investigated self-evaluated performance because real performance was impossible to obtain in real-life feedback. The scale of the questions kept the same with that in the experiment.

3.2.4. Statistical analysis methods

For the results of subjective questionnaire collected in the experiment, individual questions were categorized into different variables through data reduction techniques, i.e. reliability test and factor analysis, for further analysis. Data reduction summarizes several individual questions that may be dependent with each other into one variable that is more fundamental, which can reduce the large number of data in the questionnaire for easier and clearer interpretation. For the real-life occupant feedback, the number of subjective questions was only five, so the data was used directly without data reduction procedure.

Reliability test examines if several individual questions can represent one variable, e.g. whether all questions relating to head (clear headed, headache, heavy headed, sleepy, tired) can be used to represent “head sensation”. The judging criterion is Cronbach's alpha, which varies from 0 to 1 and tells the internal consistency of these questions. Generally speaking, good internal consistency can be expected when the Cronbach's alpha is larger than 0.7. Internal consistency is regarded as acceptable if the Cronbach's alpha is larger than 0.6. If the Cronbach's alpha is smaller than 0.5, internal consistency is regarded as unacceptable and data will be deleted.

Factor analysis further examines if the several individual questions in one variable represent one factor, or several sub-factors. The first criterion is Kaiser-Meyer-Olkin (KMO) statistics, which varies from 0 to 1.0 and should be larger than 0.6 to proceed meaningful factor analysis. When KMO is larger than 0.6, initial eigenvalues of components of the variable determine whether there is one factor or several sub-factors. If only one component has an initial eigenvalue larger than 1, this variable consists only one factor. If two or more components have initial eigenvalues larger than 1, this variable consists several factors.

Perception of SBS were summarized into different variables, i.e. “Head”, “Nose”, “Throat”, “Eyes”, “Hands”, “Skin”, “Ear”, “Breath”. For draft and thermal sensation of different body parts, two variables were established. Upper-body level is the exposed upper parts which include head, neck, and arms. Lower-body level is the exposed lower parts which include calf, ankle and feet. For the subsequent analysis, value of each variable was taken as the average of several affiliated individual questions. For overall draft sensation and thermal sensation variables, there are numerous formulas to calculate mean skin temperature by weighted or un-weighted method (Mitchell et al. 1969; Choi et al. 1997), and the un-weighted

method was used because skin temperature is different from thermal sensation, and also there's not enough evidence to support one weighted approach is superior to another. Therefore the value was taken as the average of all body parts. Most defined variables have items that are quite consistent, except for "Skin" and "Hands" as shown in Table 3.1. For factor analysis, only "Hands" and "Skin" have KMOs that are smaller than 0.6, and all variables only has one initial eigenvalue larger than 1. Therefore, variables except "Hands" and "Skin" are analysed in later sections.

Table 3.1 Results of reliability and factor analysis of variables

Variable	Number of questions	Reliability test	Factor analysis	
		Cronbach's Alpha	KMO	Initial Eigenvalue
Draft_Upper	3	0.901	0.696	2.509
Draft_Lower	3	0.927	0.708	2.621
Thermal_Upper	3	0.812	0.621	2.208
Thermal_Lower	3	0.901	0.696	2.511
Head	5	0.872	0.776	3.354
Nose	5	0.769	0.776	2.781
Throat	3	0.785	0.682	2.099
Eyes	5	0.778	0.786	2.685
Hands	2	0.578	0.500	1.425
Skin	2	0.496	0.500	1.355
Ear	3	0.783	0.682	2.105
Breath	5	0.874	0.830	3.348

Non-parametric statistical tests were used for all the variables for consistent comparisons, because many variables' distribution didn't follow the normal distribution and cannot be tested by parametric statistical tests. Related-sample Wilcoxon signed ranks test was used for data from the same human subjects (within-subject). Mann-Whitney U test was used for non-related samples (between-subject). $P < 0.05$ is taken as significant level in the discussion unless stated otherwise, and p-value below significant level implies that significant difference exists and dominates the effect of random error. For overall trend of draft

and thermal comfort, cold feet analysis, SBS, and short-term task performance, comparison was within-subject analysis, i.e. data of 28 human subjects who participated all four scenarios were used. On the other hand, in each room comparison between different zones was analysed to investigate their effects on draft and thermal sensation, therefore zone analysis was between-subject, i.e. data from those who came only either in the 1st or 2nd two-day experiment were first selected, and for those who came in all four scenarios only the data in the 1st two-day experiment were selected, and finally these two batches of data were pooled together. The comparison between MV and PDV in real-life occupant feedback was also between-subject analysis.

3.3. Experimental results and discussion

3.3.1. Environmental background

Representative environmental data in the tutorial room during the experiment are summarized in Table 3.2. As can be seen, MV room led to relatively homogeneous temperature at different height due to relatively high air velocity at diffusers. On the contrary, PDV room has significant temperature stratification at different height, and the air velocity at diffusers was much smaller, because in passive displacement ventilation fresh cool air was driven by temperature gradient rather than mechanical fans. Temperatures at 1.5m above the ground at room center (Temp I) were similar among the four scenarios, which showed the overall temperature condition in MV and PDV rooms. The temperature at ground level at room center (Temp III) in PDV II was lower compared to that in PDV I. This is mainly the combination effect of cooler outdoor air due to the rainy condition in day 3 (PDV II) and also the stratification of temperature at different height in PDV room. It is commonly known that the low air flow velocity in PDV system reduces the noise and energy consumption, but it also causes the stratification issue in the room. The temperature feedback sensor is located near the top of the ceiling, where the temperature is still

around 25°C, so the chilled water keeps flowing through the cooling coil. Combining the cooler outdoor air, it leads to the low temperature at the ground supply in PDV II. The effect of radiant temperature should be minimal, because there is no radiant panel heating or cooling system. The rooms are not exposed to sunlight, have no windows, and no radiant asymmetry exists either. The assumption that operative temperature equals air temperature holds according to ASHRAE Standard 55. For RH, the PDV room would lead to slightly lower value than the MV room. CO₂ concentration was high in MV I, and the problem was fixed afterwards in MV II. The CO₂ conditions also correlated well with the AER conditions. Daily average outdoor concentration of CO₂ was around 440 ppm. The average background noise level was between 30-40 dB.

Table 3.2 Environmental background in the tutorial room during the experiment

Scenario	MV I (day 1)	PDV I (day 2)	PDV II (day 3)	MV II (day 4)
Temp I [~] (°C)	23.6±0.2	23.2±0.3	24.0±0.2	24.3±0.8
Temp II [*] (°C)	23.7±0.1	22.4 ±0.2	21.9±0.1	24.1±0.4
Temp III [§] (°C)	22.8±0.4	20.9±0.5	17.9±0.7	23.0±1.2
Supply Temp [^] (°C)	20.5±2.8	17.5±0.7	15.5±1.8	19.8±2.6
Air velocity [@] (m/s)	4.52±0.07	0.35±0.18	0.31±0.19	4.67±0.10
RH ^{&} (%)	76.1±3.5	57.6±4.0	57.3±2.5	74.3±5.4
CO ₂ [#] (ppm)	1709-2690	< 1000	< 1000	< 1000
AER (/h)	0.78±0.03	2.22±0.09	2.24±0.08	1.65±0.07
Chilled Water Consumption (kw)	10.15±0.47	16.38±1.57	16.70±1.02	13.26±2.25

[~] Temperature at 1.5m above the ground at room center

^{*} Temperature at 0.7m above the ground at room center

[§] Temperature at ground level at room center

[^] The supply air temperature

[@] Average air velocity at diffusers

[&] Relative humidity at 1.5m above the ground at room center

Concentration during the second half (60-120min) of each session at 1.5m above ground at room center

The air velocity in the occupied zone in the field is very difficult to quantify, because it is highly location dependant. This also reflects the complexity in the field. The ranges of air velocity and temperature in the MV and PDV room in the occupied zone are shown in Table 3.3. As can be seen, the ranges of air velocity and temperature in the occupied zone are highly correlated with those at diffusers and room centers.

Table 3.3 The ranges of air velocity and temperature in the occupied zone

Location	MV Room		PDV Room	
	Temperature	Air-velocity (m/s)	Temperature	Air-velocity (m/s)
1.5m above the ground	Relatively Homogenous	0.10-1.12	Relatively Homogenous	<0.05
0.7m above the ground		<0.15	Relatively Homogenous	0.05-0.16
At ground level		<0.15	Relatively Homogenous	0.05-0.40

3.3.2. Draft sensation and acceptability: overall trend

As can be seen in Figure 3.4, MV room could lead to higher draft sensation above 4, i.e. more breezy, while the draft sensations were below 4 in PDV room. The draft sensation difference between MV and PDV was also statistically significant ($P < 0.05$). Cooling devices where outlets installed in the ceiling can lead to draft discomfort in workplaces (Griefahn et al. 2002), as high air velocity is needed to achieve relatively homogenous distribution of temperature and IAQ in the room. The significant draft sensation difference can be attributed to higher average air velocity at diffuser and higher air velocity range in the occupied zone in the MV room than those in the PDV room. The whole body draft acceptability however, did not show significant difference between MV and PDV indicating that draft comfort

was similar in both systems. Nonetheless, some insights can still be drawn from the whole body draft acceptability. As can be seen, draft acceptability was above neutral (towards very acceptable end) in the PDV room while it was slightly lower than neutral (towards very unacceptable end) in the MV room. This can be explained by lower draft in the PDV room and larger draft in the MV room. It was interesting to note that the draft acceptability in MV II was slightly higher than neutral. This may be caused by slightly higher room temperature in MV II ($24.3\pm 0.8^{\circ}\text{C}$) than that in MV I ($23.6\pm 0.2^{\circ}\text{C}$). Previous studies also showed that complaint of draft can be reduced by elevated room temperature (Griefahn et al. 2001; Toftum et al. 1996).

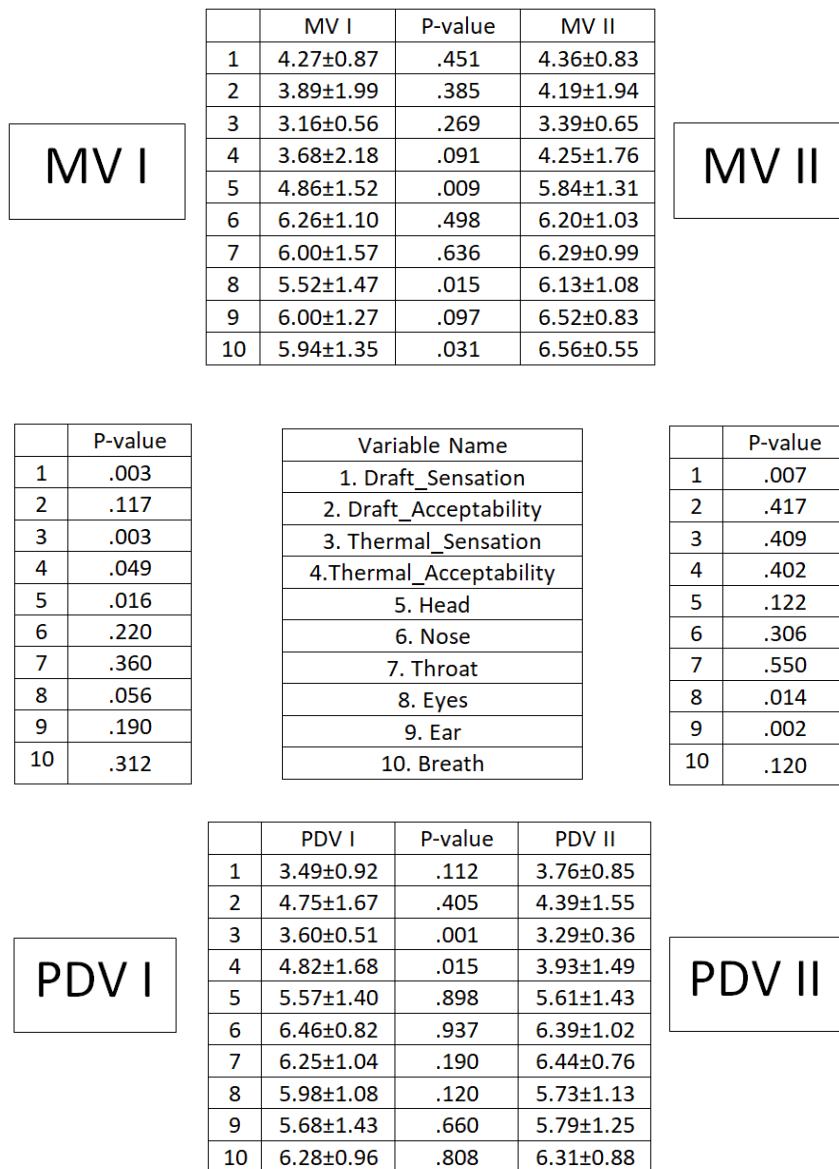


Figure 3.4 Overall trend in subjective questionnaire: (1) draft sensation: 1 refers to more still, and 7 refers to more breezy; (2) thermal sensation: 1 refers to cold, and 7 refers to hot; (3) whole body draft acceptability, whole body thermal acceptability, and SBS: 1 refers to “very unacceptable”/“very bad”, and 7 refers to “very acceptable”/“very good”.

3.3.3. Thermal sensation and acceptability: overall trend

As can be seen in Figure 3.4, all thermal sensation values were slightly below neutral, indicating that common attire of local students under normal indoor temperature set-point could lead to slightly cool thermal sensation. Therefore, slightly higher RH in the MV room (~75% RH) than that in the PDV room (~55%

RH) was considered insignificant for thermal comfort analysis, as previous studies also suggested that RH even close to 100% would not cause much discomfort among thermally neutral persons performing sedentary work (Jørn et al. 1998). Tsutsumi et al. (2007) also found that within 23-24°C room temperature range, no significant difference existed in thermal sensation and humidity sensation among RH ranging from 30-70%.

The whole body thermal acceptability of MV I was below neutral (towards very unacceptable) while the whole body thermal acceptability of PDV I was above neutral (toward very acceptable), and the difference was significant. This indicated that overall thermal condition in PDV I was more acceptable than that in MV I. Although the temperatures at 1.5m above the ground at room center of both MV I and PDV I were nearly the same, higher draft (which could lead to lower thermal sensation) might lead to the significantly lower thermal acceptability in MV I.

Between MV I and MV II, overall thermal sensation did not show significant difference. For whole body thermal acceptability, the significant level was slightly above 0.05 (still below 0.1) between MV I and MV II, which suggested that MV II was slightly more acceptable. This may be attributed to the higher room temperature in MV II ($24.3\pm 0.8^{\circ}\text{C}$) than that in MV I ($23.6\pm 0.2^{\circ}\text{C}$) which compensated discomfort caused by higher draft.

Significant differences in overall thermal sensation and whole body thermal acceptability were observed between PDV I and PDV II. As can be seen, PDV II showed colder thermal sensation and was less acceptable than PDV I. Lower temperature at ground level in PDV II ($17.9\pm 0.7^{\circ}\text{C}$) than that in PDV I ($20.9\pm 0.5^{\circ}\text{C}$) was believed to be the dominant reason.

Unlike the comparison between MV I and PDV I, no significant differences in the overall thermal sensation and acceptability were observed between MV II and PDV II. As discussed above, higher room temperature in MV II ($24.3\pm 0.8^{\circ}\text{C}$) compensated cold sensation caused by higher draft while lower temperature at ground level in PDV II ($17.9\pm 0.7^{\circ}\text{C}$) enhanced colder feeling. As a result, the overall thermal sensation difference between MV II and PDV II was only 0.1, which consequently led to insignificant whole body thermal acceptability difference. These results suggested that whole body thermal acceptability was more related to the overall thermal sensation which is governed by temperature, humidity, and draft.

3.3.4. Draft and thermal sensation: cold feet effect

As can be seen in Table 3.4, draft and thermal sensation also showed significant patterns at different body levels. In the PDV room, draft sensation of lower body level was significantly larger than that of upper body level. This was because the diffusers in the PDV room were located at the ground level. Thermal sensation of lower body level in the PDV room was also significantly colder than that of upper body level. This was the cold feet effect often observed in displacement ventilation.

In the MV room, draft sensation between upper level and lower level did not show significant difference, and all values were above neutral. On the other hand, thermal sensation differed significantly between upper and lower body level in the MV room (though in MV II the significant level was slightly above 0.05, but still below 0.1), and thermal sensations were all below neutral. This suggested that although the general temperature situation did not differ too much at different height in MV room, cold feet effect can still occur, which may be due to that human's feet are generally more sensitive to cold than upper body parts (Zaproudina et al. 2011).

Table 3.4 Cold feet effect: (1) draft sensation: 1 refers to more still, and 7 refers to more breezy; (2) thermal sensation: 1 refers to cold, and 7 refers to hot.

Variable	PDV I	PDV II	MV I	MV II
Draft_Upper	2.70±1.13	2.95±1.07	4.54±1.28	4.58±1.39
Draft_Lower	5.17±1.43	5.51±1.29	4.90±1.50	4.67±1.31
Draft_P-value	<0.001	<0.001	0.394	0.649
Thermal_Upper	4.10±0.49	3.74±0.38	3.25±0.75	3.30±1.02
Thermal_Lower	2.26±0.94	2.02±0.81	2.40±0.89	2.92±1.00
Thermal_P-value	<0.001	<0.001	0.001	0.058

3.3.5. Draft and thermal sensation: zone analysis

Although homogeneous mixing in horizontal direction is a common assumption in architecture design, difference between zones may exist in actual indoor environment. Figure 3.1 shows the classification of occupied seats for zone analysis. Solid circles (SC) refer to seats that led to larger draft sensation or colder thermal sensation, and hollow circles (HC) refer to the opposite. For the MV room, the classification depends on: (1) center-to-center distance from overhead conditioner to occupied seats (0.5m-2m is assumed to result in larger draft sensation or colder thermal sensation); (2) direction of draft (whether it is direct or oblique to human subjects, and direct draft is assumed to result in larger draft sensation or colder thermal sensation). Only sensation of upper body level was considered for the MV room because the diffusers are on the ceiling. For the PDV room, since the distances from occupied seats to diffusers on the floor are more or less similar, the classification mainly depends on the direction of draft, and only lower body level's sensation was considered. The results in Table 3.5 showed significant differences between different groups of seats in terms of draft and thermal sensation, which suggested that the positions and seats arrangement can lead to inhomogeneous sensations at different locations in a room.

Table 3.5 Zone analysis: (1) draft sensation: 1 refers to more still, and 7 refers to more breezy; (2) thermal sensation: 1 refers to cold, and 7 refers to hot.

MV Room					
Draft Sensation			Thermal Sensation		
SC seats	HC seats	P-value	SC seats	HC seats	P-value
5.03 ±1.16	3.83±1.07	0.001	2.89±0.77	3.46±0.55	0.006
PDV Room					
Draft Sensation			Thermal Sensation		
SC seats	HC seats	P-value	SC seats	HC seats	P-value
5.75 ±1.04	4.61±1.43	0.003	1.75±0.78	2.44±0.80	0.004

3.3.6. Sick building syndromes

As can be seen in Figure 3.4, all physiological variables were above neutral level, which suggested that SBS were generally not severe even in the worst case scenario. Nonetheless, improvement in SBS can be observed when the environment was improved. Three major variables showed significant patterns: head sensation, breath sensation, and eye sensation. For other SBS variables, no significant differences existed among different scenarios.

For SBS related to head, improved feeling could be found in PDV I or MV II when compared with MV I, while no significant differences were observed between MV II and PDV II and between PDV I and PDV II. This suggested higher CO₂ concentration in MV I was the main cause of SBS related to head. Other factors such as draft, temperature, and RH did not seem to contribute to SBS related to head that much at least in the range tested in current study.

For SBS related to eyes, improved feeling could be found in PDV I or MV II as compared to MV I. This may be attributed to higher CO₂ concentration in MV I. Exposures to air pollution have long been correlated with ocular surface irritation, resulting in symptoms of hyperemia, swelling, tearing, and dry eye sensation (Basu 1972), and recent studies also showed that high levels of exposure to dust or CO₂

could lead to eye irritation (Kjaergaard et al. 2004; Tsai et al. 2012). Improved feeling could also be observed in MV II when compared with PDV II. This could be caused by higher RH in the MV room than that in the PDV room. Previous studies showed that dry air could cause reduced tear film stability (Kjaergaard et al. 2004), and another study involving 3,154 Taiwanese workers showed that RH around 55% could lead to higher prevalence of dry symptoms of the eye than RH around 65%, indicating that for workers living in a high humidity environment such as Taiwan, the relatively low humidity condition could still cause dry eye symptoms (Su et al. 2009). SBS resulted from low RH can also be found in temperate climate zones, as shown in the review study by Wolkoff (2008), and the threshold of low RH causing eye discomfort in temperate climate zones could be lower (RH ranging from 10-30%). This suggested that the lower RH than the typical ambient level can lead to eye-related SBS, though the range varies from one climate zone to another.

3.3.7. Short-term performance

Figure 3.5 shows the results of short-term performance in the four scenarios. For short-term memory tasks, values were accurate answers per minute (Glickman et al. 2005). For other tasks that cannot be finished within given time, values listed were total accurate answers. Because paired (within subjects) statistical test was used for performance analysis, variations of strategies among different human subjects to answer questions do not matter much.

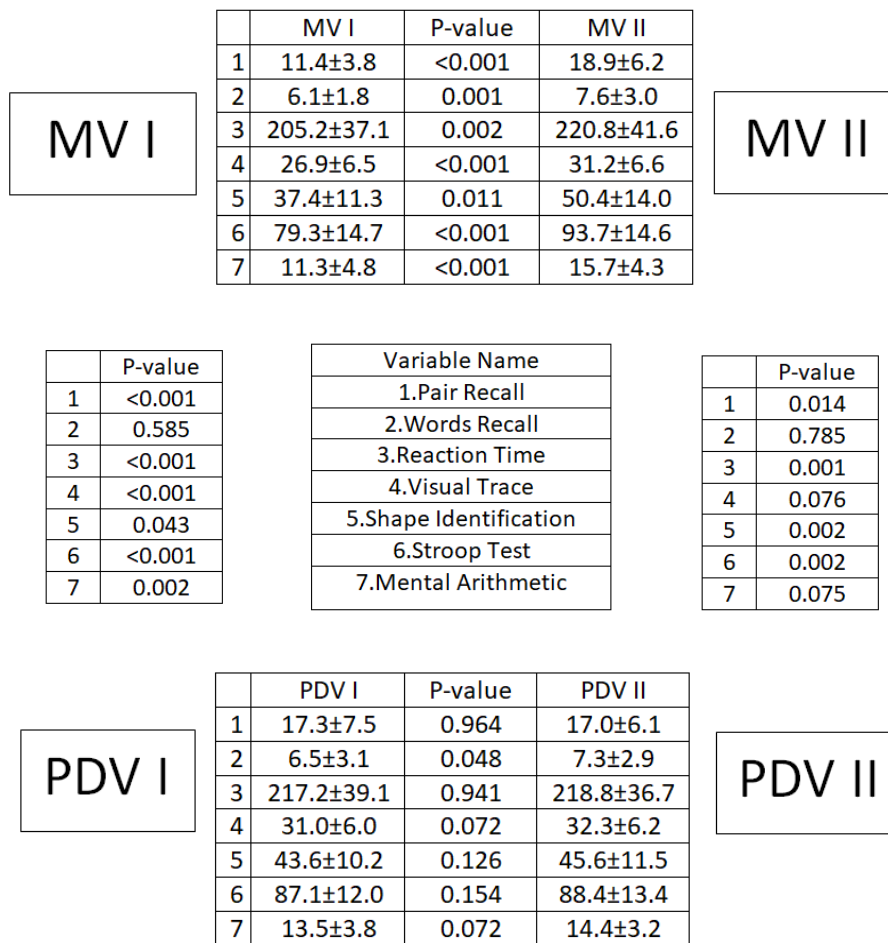


Figure 3.5 Results of short-term performance: values are accurate answers per minute (short-term memory tasks) or total accurate answers (other tasks)

As can be seen, MV II or PDV I led to significantly improved performance of human subjects than MV I. This should be mainly attributed to lower CO₂ concentration in MV II or PDV I, which could lead to less SBS related to head and eyes as discussed in previous section, and consequently improved performance. Some previous studies also showed that both CO₂ and/or other indoor air pollutants (Wyon 2004; Satish et al. 2012), can have negative impact on perceived air quality and work performance. Less eye irritation symptom could also improve work performance (Wolkoff 2008). Occupants in MV II also performed better in some tasks than those in PDV II. This should mainly due to less SBS related to eyes in MV II, as a result of higher RH in MV II as discussed above.

3.4. Real-life occupant feedback results and discussion

After the four-day experiment, a real-life occupant feedback was conducted for two months and Table 3.6 shows the results. MV room had 71 data points and PDV room had 88 data points. As can be seen, perceived health in PDV was better than that in MV with significant difference. For perceived IAQ and performance, occupants in PDV room felt better with the p-value below or around 0.1 (though higher than 0.05). For thermal and draft sensation, the draft sensation was higher in MV than that in PDV and thermal sensation was lower in MV than that in PDV although the p-value was not significant.

As can be seen, the general patterns of the results in both the experiment and real-life feedback were similar, though the significance level of results in real-life occupant feedback was not as strong as that in the experiment. The main reason was that the real-life feedback was conducted in a less controlled condition (e.g. attire of occupants, types of working contents), as compared with the experiment. In real-life feedback, students in MV were also different from those in PDV, in contrast to the experiment in which same group of human subjects experienced both rooms. All these reasons led to larger variability of the data and weaker statistical significance in real-life occupant feedback.

Table 3.6 Results of real-life occupant feedback: (1) draft sensation: 1 refers to more still, and 7 refers to more breezy; (2) thermal sensation: 1 refers to cold, and 7 refers to hot; (3) perceived IAQ, health and performance: 1 refers to “very bad”, and 7 refers to “very good”.

	Draft sensation	Thermal sensation	Perceived IAQ	Perceived health	Perceived performance
MV	3.90±1.46	3.48±1.54	3.37±1.56	3.80±1.58	3.66±1.47
PDV	3.83±1.56	3.80±1.63	3.88±1.87	4.43±1.98	4.09±1.74
P-value	0.830	0.210	0.092	0.020	0.101

3.5. Conclusions and outlook

In this study, a field experiment using subjective questionnaires and computerized task-based tests was conducted in two tutorial rooms to quantitatively compare students' thermal sensation, sick building syndromes (SBS), and short-term performance under mixing ventilation (MV) system and passive displacement ventilation (PDV) system. Feedback from real-life occupants using tablet device further complemented the experiment. Main conclusions from this study include:

- MV could lead to significantly larger draft sensation than PDV due to high air velocity from the overhead diffusers. However, different ventilation systems did not cause significant difference in whole body draft acceptability.
- PDV led to significantly higher draft and colder sensation in the lower body level because the diffusers in the PDV room were located at the ground level. On the contrary, draft distribution was perceived relatively homogenous in vertical direction in the MV room.
- Seat arrangement, e.g. location and orientation, could lead to inhomogeneous sensations in a room. Larger draft and colder sensations were significant in both MV and PDV rooms if the locations were within certain range and facing directly to diffusers.
- Higher CO₂ concentration was the main factor causing SBS related to head while both higher CO₂ concentration and lower RH contributed to SBS related to eye. As a consequence, SBS resulted from high CO₂ concentration and low RH could lead to decrease in short-term performance.
- General patterns of the results in both the experiment and real-life feedback were similar, though the significance level of results in real-life occupant feedback was not as strong as that in the experiment.

Measures were taken to minimize learning effects. Other types of sequential effect such as fatigue effect might exist, but it was not expected to affect the results much, as judged from the final results. Draft could cause cold feeling and was a significant issue for both MV and PDV since the indoor space in this study is relatively small and diffusers are close to occupants. Apart from proper design of the ventilation system, careful room layout including thoughtful seating and diffusers arrangement should also be taken into consideration. Although the FCU is designed with ventilation mechanism, the effectiveness in the actual environment needs to be confirmed during installation. The poor ventilation design of MV should be avoided in practice, as later investigations of other MV system rooms on the same campus also revealed similar high CO₂ concentration problems. On the other hand, the results could be different in other environmental settings, e.g. office environment, which could be a potential future work. Some study has shown that the economic benefit of health improvement from better indoor environment exceeds costs by a factor of 18 to 47 (Fisk et al. 1997). Other study suggested that the salaries of workers exceed the building energy and maintenance costs by approximately a factor of 100 (Fisk 2000). Therefore this issue is not only related to the wellbeing of building occupants, but also has economic consequences.

Chapter 4 Impacts of indoor environmental quality on students' wellbeing and performance through life cycle costing perspective

4.1. Overview

This chapter evaluates the impacts of indoor environmental quality on students' wellbeing and performance in educational building with other major building metrics. This is a life cycle costing (LCC) case study based on the experimental results from Chapter 3. Specifically, the indoor environmental quality impacts on students were quantified into different metrics and these metrics were then monetized. Different weighting schemes for the metrics were explored through LCC perspective, and sensitivity analysis was conducted for various uncertainties.

4.2. Methodology

4.2.1. Scope

For the experimental study in Chapter 3, no change was made to the PDV room, and the two PDV scenarios were essentially the same, both having normal ventilation rates and CO₂ concentration. Therefore in this study, the first PDV scenario was excluded, and the three remaining scenarios were considered, denoted as MV IAQ 1 (poor IAQ), MV IAQ 2 (good IAQ), and PDV. These three scenarios mainly differed in the capital cost of air-conditioning and mechanical ventilation (ACMV) systems, operational energy consumption, and IEQ and its impact on building occupants. Other aspects in the construction, operation & maintenance and demolition stages were considered essentially the same.

In Chapter 3, in addition to the well-controlled experiment, a real-life occupant feedback with a much larger student population was also conducted for two months in the same two tutorial rooms to further complement and corroborate the experimental results, and the results in the real-life feedback were generally in

accordance with the results in the experiment. Therefore only the experimental results would be used in this chapter, as they were much more detailed and could still represent responses of a much wider student population.

In addition to the data in Chapter 3, the capital costs of the two ACMV systems were further collected from the University's facility management department, with SGD 13,200 for MV system, and SGD 23,800 for PDV system. The cost of the extra fan and additional equipment added to the MV IAQ 2 scenario during the experiment was less than SGD 200, and the energy consumption of the fan was less than 100 W.

In this chapter, the data from the experiment would be used to establish the link between IEQ and the two impact categories, namely students' wellbeing and performance. The metrics used to quantify wellbeing of the building occupants would be the number of sick leave days, and the indicator to quantify performance would be the weighted average marks (WAM). The monetized metrics for these two impact categories would be benefit of avoided sick leave and benefit of WAM respectively. The overall LCC framework is illustrated in Figure 4.1. The MV IAQ 1 scenario was also found in other MV system rooms on the same campus and therefore would be used as reference. Therefore only the main metrics that were different among the three scenarios are shown in Figure 4.1.

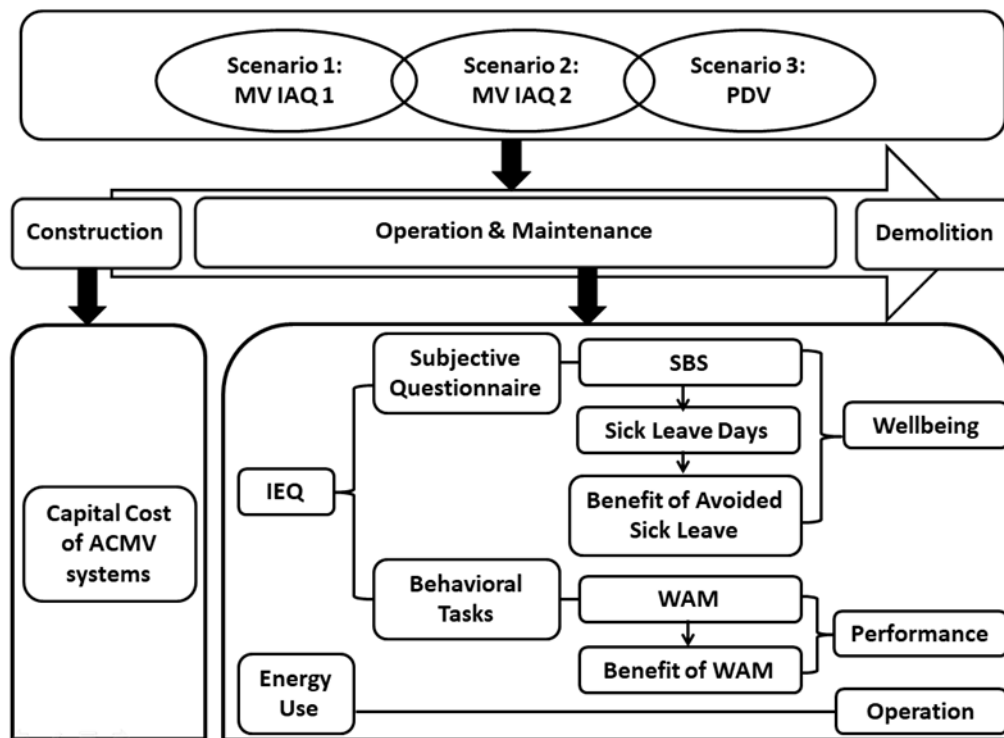


Figure 4.1 Scope and framework for the three scenarios

4.2.2. Quantification and monetization of indoor environmental impacts on occupants

4.2.2.1. Sick building syndromes, sick leave days and the costs

The report “Health Optimization Protocol for Energy-Efficient Buildings” (HOPE 2005) under the program “Energy, Environment, and Sustainable Development” by the European Community defined Building Symptoms Index (BSI) as the mean number of acute health symptoms closely related to SBS. A total of 10 fundamental symptoms are counted for the BSI₁₀. The ten symptoms are:

- Dry eyes
- Itching/watering eyes
- Blocked/stuffy nose
- Runny nose
- Dry/irritated throat
- Headache
- Tiredness/lethargy
- Flu-like symptoms
- Breathing difficulty
- Chest tightness

Sick leave is another indicator that has been widely used to study the indoor environment (Milton et al. 2000), which can be measured by the number of spells and the number of days of sick leave (Raw 1992). Number of spell counts the number of people that report sick leave only, not specific sick leave days. In general, respiratory illnesses account for a large fraction of sick leaves (Milton et al. 2000). Fisk et al. (2005) further confirmed this and stated that short-term sick leave was proportional to the prevalence of respiratory illnesses. Six respiratory symptoms from BSI₁₀ were considered important, which were blocked/stuffy nose, runny nose, dry/irritated throat, flu-like symptoms, breathing difficulty, and chest tightness. Clark et al. (2004) in his research on impacts of asthma to school absenteeism also included cough as a major asthma symptom. Additionally, headache was considered as another symptom outside the respiratory symptoms which might make students report absenteeism and was therefore included in the computation. From these literatures, eight symptoms from BSI₁₀ were chosen to calculate sick leave, excluding dry eyes and itching/watering eyes.

Raw (1992) conducted a statistical analysis of staff absence records, and his method was used in this study. He found out that there was a relationship between the numbers of SBS occurred among workers and the sickness absences; i.e. there was only very minimal changes in sickness absence until workers reported four or more symptoms. He concluded his research by highlighting that sickness absence would only be expected if this score is exceeded. In the previous tutorial rooms experiment, there were no data on how frequently the symptoms occurred. The methods were thus modified accordingly. As the subjective questionnaire in the experiment used 1-7 scale, if the respondent answered a particular SBS question with '4' and below, it was counted as one symptom occurred. Otherwise, it was counted as no symptom. It was further assumed in the current study that if a student reported four or more

symptoms out of the eight symptoms mentioned above, the student would report a sick leave.

To further calculate the number of days of sick leave, Milton et al. (2000) conducted an analysis among 600 office workers and studied the employees' absence data for one calendar year. The average CO₂ level in the office was at 800-900 ppm. The study concluded that the indoor air quality accounted for 1.2 to 1.9 days of increased short-term sick leave per person per year. This indoor air quality was most similar to that of MV IAQ 2 scenario. Therefore, the number of days of sick leave taken by students in MV IAQ 2 scenario was assumed to be the same as the value in the study, i.e. 1.2 to 1.9 days of sick leave per person per year, or averaged to be 1.55 days/person/year. As the number of students in the tutorial rooms is fixed by the room capacity, for the other two scenarios the values can be estimated by using the proportion of the percentage of population reporting sick leave. The numbers of sick leave days are shown in Table 4.1. It can be seen that for a given number of students, PDV scenario had the least amount of sick leave days, while the MV IAQ 1 had the most amount of sick leave days.

Table 4.1 Sick leave indicator results

	MV IAQ 1	MV IAQ 2	PDV
Number of subjects reporting sick leave (≥ 4 symptoms in the experiment)	6	2	1
Percentage of population (out of total subjects in the experiment)	15.38%	5.13%	2.56%
No. of total off days due to sick leave for a given room capacity, e.g. 30 students (days/year)	$15.38/5.13 \times 46.5 = 139.4$	$30 \times 1.55 = 46.5$	$2.56/5.13 \times 46.5 = 23.2$
Normalizing by these 30 students, (days/person/year)	4.65	1.55	0.77
Total cost of sick leave	565.35	188.45	94.22

(SGD/person/year)			
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Sick leave days were then monetized. Cost of sick leave is the amount of dollars that is lost or has to be spent for every day of sick leave. This value was assumed to be proportional to the number of sick leave days. Many previous studies were based on office setting, and monetization was made by calculating the amount of employee's salary per day and additional medical fees for the employee if there was a health insurance provided by the employer. As for students, a more relevant literature review was conducted to find out the costs, which were categorized to three different costs as shown in Table 4.2. The total value sums to SGD121.58, or approximately SGD122 per day of sick leave. Together with the sick leave days in Table 4.1, the costs of sick leave per person per year in each scenario are shown in Table 4.1.

Table 4.2 Different types of costs of sick leave

Breakdown of costs of sick leave	Approximate Value (SGD)
<ul style="list-style-type: none"> Capital cost, i.e. the amount of tuition fee that has been paid and is lost due to absence from school. This is based on average annual tuition fee of SGD10, 775 (NTU, 2014) and 150 school days per year. 	71.83
<ul style="list-style-type: none"> Direct cost, i.e. the average amount of medical expenses students have to pay for consultation in clinics/polyclinics (Singhealth Polyclinics, 2014; National Health Group Polyclinics, 2013). 	18.38
<ul style="list-style-type: none"> Indirect cost, i.e. the average amount of subsidy provided by government for each consultation at clinics/polyclinics (Singhealth Polyclinics, 2014; National Health Group Polyclinics, 2013). 	31.38
Total	121.58 (\approx 122.0)

4.2.2.2. *Weighted average mark and the benefits*

Average scores or grades have been used widely and accepted in most schools and colleges to measure performance. The results from the computerized tasks in the previous experiment would be used as substitutes for students' grades, as these computerized tasks measure different aspects of mental activities and therefore the performance in these tasks was regarded to be correlated to the real-life grades.

There are many methods to compute students' average grades. Many colleges and universities use Grade Point Average (GPA). This is done by converting numeric scores to letter grades that correspond to a grade point. In colleges in Australia, weighted average marks (WAM) system is used, where the weights are assigned directly to the numeric scores instead of the grade points. The final WAM will be numeric scores out of 100. In this study, the numeric scores similar to WAM would be used for simplicity and to avoid any inaccuracy that might arise for conversions to grade points. Furthermore, it was assumed that different tasks contributed equally to represent students' performance in the experiment, and therefore they were assigned equal weights. All scores were then normalized out of 100.

The benefit of WAM were then monetized to better compare with other impact categories and to fit into the LCC framework. The WAM have great impact on students' income after they graduate and enter the workforce. It has been shown in many studies that there is a positive relationship between students' performance and starting salary. These studies concluded that students with higher GPA or final marks have a tendency to receive higher starting salary. A summary of the literatures is shown in Table 4.3.

Table 4.3 Summary of literatures on student performance and starting salary

% Salary increase per unit marks	Location of study	Year of study	Student population	Source
----------------------------------	-------------------	---------------	--------------------	--------

5 % per 1 point of GPA increase	USA	1983-1984	Female students	Rumberger et al., 1993
8.9 % per 1 point of GPA increase	USA	1982-1985	Business major	Jones et al., 1990
9 % per 1 point of GPA increase	USA	1983-1984	Science & maths major	Rumberger et al., 1993
10 % per 1 point of GPA increase	USA	1983-1984	Business & education major	Rumberger et al., 1993
0.68 % per 1 mark increase	West Australia	2002-2004	University of Western Australia students	Chia et al., 2008

In this study, the final marks were not associated with gender or any college major. Furthermore, the marks in this study were also normalized out of 100, which is similar to the WAM in Australia. Thus the increase in salary per one mark of 0.68 % from Chia et al. (2008) in Table 4.3 was assumed to be relevant in this study, as the study by Chia et al. (2008) also comprised the general student population regardless of gender and college major.

Data of starting salary of NTU graduates are available from the Singapore Ministry of Education (MOE) Graduate Employment Survey 2013. The average starting salary of all students across all majors was computed proportionally based on the number of students. The weighted average monthly starting salary was estimated to be approximately SGD 3,107. This equaled to an annual starting salary of approximately SGD 37,280, which was set as baseline. The percentage difference in annual starting salary from this baseline can be obtained by computing how much the score in each scenario deviates from the baseline score and multiplied by 0.68 % change in starting salary per 1 mark difference. The normalized scores and the corresponding starting salaries are shown in Table 4.4.

Table 4.4 Normalized scores and annual starting salary

	MV IAQ 1	MV IAQ 2	PDV
Average scores, out of 100	50.25	62.32	58.19

Average (baseline score)	56.92		
Starting salary in each scenario (SGD/year)	35,589	38,649	37,602

4.2.3. Weighting schemes

One way to guide decision making is by assigning weights to different metrics, as was done by Mansour et al. (2013) in his social life cycle study on material selection for a building. Only the final monetized metrics, i.e. ACMV capital expenses, energy expenses, benefit of avoided sick leave days and benefit of increased average marks, were used in this section. Other intermediary metrics were not used here to avoid double counting. For the weighting schemes of metrics, higher weight meant that this metric was considered more important. For instance, schemes b and c in Table 4.5 are more close to the reality, as capital and energy are mostly considered but wellbeing and performance are scarcely considered. There is no fixed rule of assigning weights because the importance of each metric is highly subjective to each individual and stakeholder. The weighting schemes of metrics are shown in Table 4.5. The sum of weights was chosen as 4 for simpler calculation.

Table 4.5 Weighting schemes of metrics. Higher weight refers to more important, and the sum of weights is 4.

Metrics	Weighting schemes of metrics				
	a	b	c	d	e
ACMV capital expenses	1	3	1/3	1/3	1/3
Energy expenses	1	1/3	3	1/3	1/3
Benefit of avoided sick leave days	1	1/3	1/3	3	1/3
Benefit of increased average marks	1	1/3	1/3	1/3	3

4.2.4. Life cycle costing

The weighting schemes in Table 4.5 were studied in details through building lifecycle perspective. Monetized metrics were used for LCC calculations.

In real-life situation, the two tutorial rooms are used daily by different students. Therefore, the impacts of tutorial rooms' IEQ as shown in the two-hour sessions in the previous experiment are actually experienced by different groups of students (morning and afternoon groups). Each group of students therefore will only be affected partially; i.e. they will only be affected during the time when they are in these two tutorial rooms. Counting and accumulating all the impacts among different groups of students is impractical. In order to pool these partial impacts, an equivalent model is needed. It was observed that the two tutorial rooms are constantly under use during school days, and the capacity for both rooms is 36 students. Therefore, a group of 30 hypothetical students (baseline scenario) was used as equivalence for each room scenario, and this group would spend all their study time in that scenario. Furthermore, the final weighted average mark (will be discussed in Section 3.2) for students is the average mark in their entire 4 years. Therefore for each 4-year cycle, the equivalent model was further simplified such that this group of 30 hypothetical students would spend their 4-year school time in that scenario and then graduate.

It should be noted that the simplification was only to pool the partial impacts spread among different groups of students of different stages to one group for each room scenario, as the impacts used for the subsequent analysis would still come from the results of the two-hour sessions in the previous experiment that is representative of the real-life situation. Furthermore, the number of people in each of the two-hour session in the previous experiment only reached half of the room capacity, so the impacts estimated from the experiment would be lower bounds, because in real-life situation more people in the room will lead to even poorer IAQ and worse impacts on wellbeing and performance. In this study a moderate service life of 32-year was used for baseline scenario for conservative purpose.

In LCC, it is necessary to calculate the present value of the future values (or vice versa). This is done to make a reasonable, unbiased assessment by discounting the future dollar terms to the present dollar terms for fair analysis. One commonly used discounting rate is the interest rate set by the central bank. In Singapore, the savings interest rate is 0.14% per year (Monetary Authority of Singapore 2016).

4.2.4.1. Life cycle costing of sick leave

Eqn. 4.1 was used for calculating the total cost of sick leave in the building lifespan.

$$\text{Total cost of sick leave} = N \times \sum_{t=1}^T C \left(\frac{1}{1+I} \right)^t \quad (4.1)$$

where N is number of hypothetical students ($N = 30$ for the baseline scenario); T is service life years of the tutorial rooms ($T = 32$ for the baseline scenario); C is average annual cost of sick leave per student (present value); and I is interest rate.

It should be noted that in Eqn. 4.1, potential inflation of the sick leave costs due to potential inflation of tuition fees and medical costs were not considered. Therefore, the value calculated by Eqn. 4.1 would be the lower bound, which means the present value of the sick leave costs could be even higher.

4.2.4.2. Life cycle costing of weighted average mark

For the baseline scenario, only the first year's salary after graduation was considered. The potential continuing income differences in the student's lifetime due to different starting salaries were ignored for conservative purpose. The wage growth rate was also ignored for conservative purpose. The salary income in the future would be discounted as shown in Eqn. 4.2.

$$\text{Total benefit of weighted average marks} = N \times \sum_{M=1}^{T/4} \sum_{t=1}^{S_t} S \left(\frac{1}{1+I} \right)^{4 \times M + S_t} \quad (4.2)$$

where N is number of hypothetical students ($N = 30$ for the baseline scenario); M is one 4-year cycle to count average marks; T is service life years of the tutorial rooms ($T = 32$ for the baseline scenario); S_t is number of years of salary to be considered ($S_t = 1$ for the baseline scenario); S is average starting salary per student (present value); and I is interest rate.

4.2.4.3. Life cycle costing of ACMV capital expense and energy expense

The capital costs of the ACMV systems were one-time present values, therefore do not need to be discounted to the present. Energy bills are expected in the entire service lifespan of the tutorial rooms and therefore need to be discounted to the present values. The Energy Market Authority in Singapore (EMA 2017) published the electricity tariffs increase in the latest quarter as 5.7 % as compared with previous year's counterpart, and the most recent electricity tariff is SGD 0.2/kWh. This growth rate is already much higher than the inflation rate, which is below 1.5 % in recent years in Singapore (Monetary Authority of Singapore 2016). Therefore to be conservative 5.7 % would be used for annual growth rate of electricity tariff. The number of total school days per year is about 150, and the average operation hours of tutorial room facilities in each school day was estimated to be 8 hours. The total costs of electricity bills in the future would be discounted to the present value as shown in Eqn. 4.3.

$$\text{Total electricity bills} = \sum_{t=1}^T C \left(\frac{1+X_{energy}}{1+I} \right)^t \quad (4.3)$$

where T is service life years for the tutorial rooms ($T = 32$ for the baseline scenario); C is annual costs of electricity bills (present value); X_{energy} is average annual growth rate of electricity tariff; and I is interest rate.

4.2.5. Sensitivity analysis

Sensitivity analysis was conducted by assigning higher and lower factors to various important metrics. Although the metrics were already conservatively estimated, sensitivity analysis can further investigate how the results will change accordingly if the metrics deviate from the baseline estimation. The metrics for baseline and sensitivity analysis are shown in Table 4.6. For most metrics, the range for sensitivity analysis was $\pm 50\%$. For the room service life and the number of students, $\pm 50\%$ is impractical and therefore the range would be within the possible maximum. For the interest rate, since the baseline value is very small, a value higher than 50% would be used for higher bound testing. For the avoided sick leave days and average marks, sensitivity factors would be applied to the differences relative to the lowest baseline values (for the sick leave days metric PDV has the lowest baseline value, and for the average marks metric MV IAQ 1 has the lowest baseline value), and therefore lower factor means the differences among three scenarios would be smaller.

Table 4.6 Metrics for baseline and sensitivity analysis

Metrics	Lower bound	Baseline	Upper bound
Interest rate (%)	0.10	0.14	1.0
Room service life (years)	24	32	40
Energy tariff growth rate (%)	3	5.7	9
Years of salary (years)	0.5	1	1.5
Number of students	25	30	35
Change of sick leave days difference relative to the lowest baseline value (%)	-50	0	50
Change of average marks difference relative to the lowest baseline value (%)	-50	0	50

4.3. Results and discussion

A summary of metrics as illustrated in previous sections is shown in Figure 4.2. The MV IAQ 1 scenario was normalized as 100%, and the other two scenarios were plotted against it. In general, better wellbeing and work performance require more

investment in capital and energy.

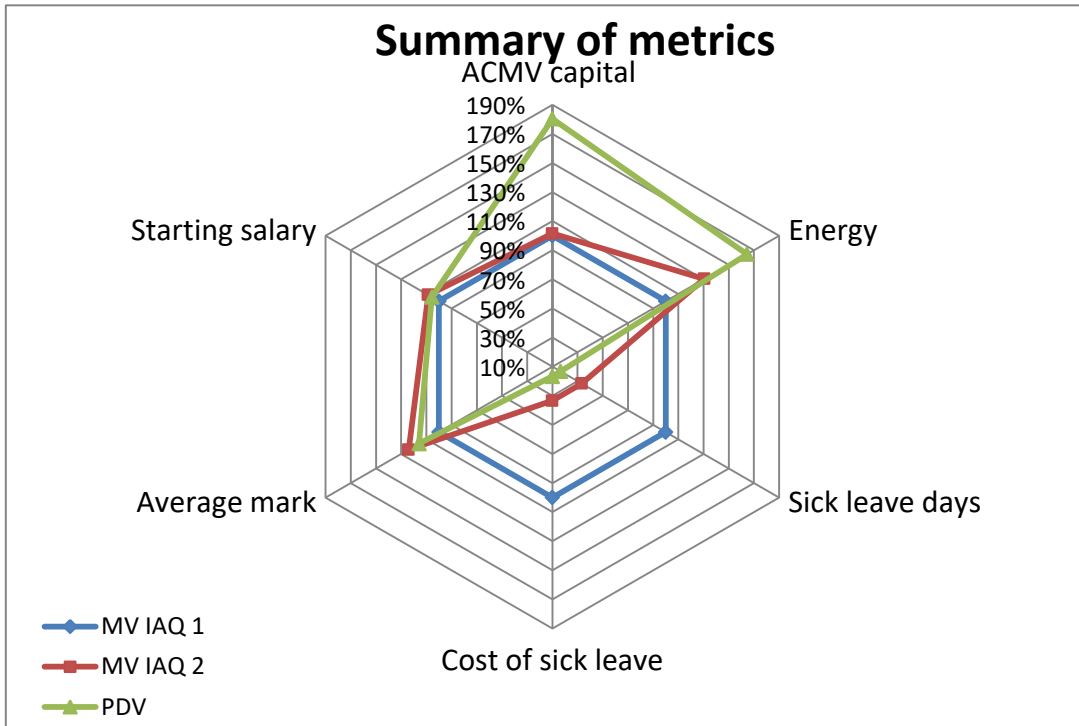


Figure 4.2 Summary of metrics. MV IAQ 1 is normalized as 100%.

4.3.1. Life cycle costing

The life cycle costing of five schemes was calculated. The MV IAQ 1 scenario was used as reference, and therefore all computed values for the MV IAQ 2 scenario and PDV scenario are relative values to the MV IAQ 1 scenario.

The baseline results of balanced scheme a are shown in Figure 4.3, where the extra expenses are negative and the resulting benefits are positive, and the total net benefit is the summation of all the benefits and extra expenses. The benefits to extra expenses ratio is the absolute value of the ratio between all the benefits to all the extra expenses. As can be seen, the extra operational energy expenses are much more than the extra capital expenses. The PDV scenario has more benefit of avoided sick leave, while the MV IAQ 2 scenario has more benefit of increased average mark. The MV IAQ 2 scenario also has more total net benefit, and the main

contributor is the benefit of increased average mark. For the benefits to extra expenses ratios, the MV IAQ 2 scenario has a larger ratio than the PDV scenario (15.7 as compared to 6.1), which is mainly due to the lower extra expenses in MV IAQ 2 scenario. In general, after the incorporation of students' wellbeing and performance, both the two improved scenarios can lead to significant net benefits, and the improvement carried out in the MV room has even larger benefits to expenses ratio due to less extra expenses.

The results of four different weighting schemes are shown in Figures 4.4 to 4.7. For scheme b, higher weight on the capital expenses leads to higher evaluation of capital expenses and lower evaluation of benefits. The general shape of the graph is similar to that of balanced scheme a, because the magnitude of one-time capital expenses is relatively small compared with other metrics. The benefits to extra expenses ratios are also similar to those of balanced scheme a.

For scheme c, higher weight on the energy leads to higher evaluation of energy and lower evaluation of benefits. Because the service life energy expense is larger than capital expense, this reduces the benefits to extra expenses ratio of MV IAQ 2 scenario to only 2.1. Furthermore, the benefits to extra expenses ratio of PDV scenario drops below 1, meaning that it has negative total net benefit. These results suggest that if service life energy expense is the primary concern in practice and higher weight is given, then the net benefits of wellbeing and performance are almost negligible or even negative.

For scheme d and e, higher weights on the wellbeing or performance lead to higher evaluation of the corresponding categories and lower evaluation of expenses. When more weight is given to wellbeing, PDV scenario has more total net benefit. When more weight is given to performance, MV IAQ 2 has more total net benefit.

Because in the balanced scheme a, the benefits of wellbeing and performance are already larger than extra expenses, higher weights for wellbeing and performance therefore further increase the benefit to extra expenses ratios.

Schemes b and c are more close to the real life practice where resources and energy are mostly concerned. On the other hand, schemes d and e might put too much emphasis on occupants. Therefore in reality weights should be more or less similar to the balanced scheme a, i.e. building metrics and human metrics should be considered as equally important.

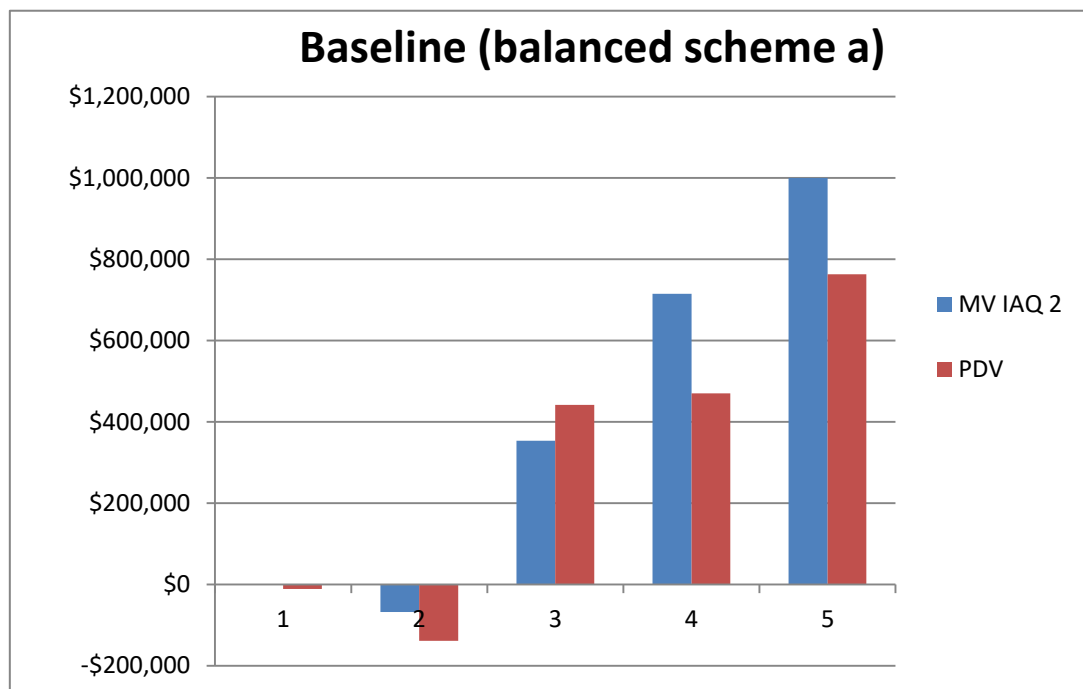


Figure 4.3 Baseline (balanced scheme a): 1: Extra ACMV capital expenses; 2: Extra operational energy expenses; 3: Benefits of avoided sick leave; 4: Benefits of increased average mark; 5: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2: 15.7; (b) PDV: 6.1. All values are relative to the MV IAQ 1 scenario.

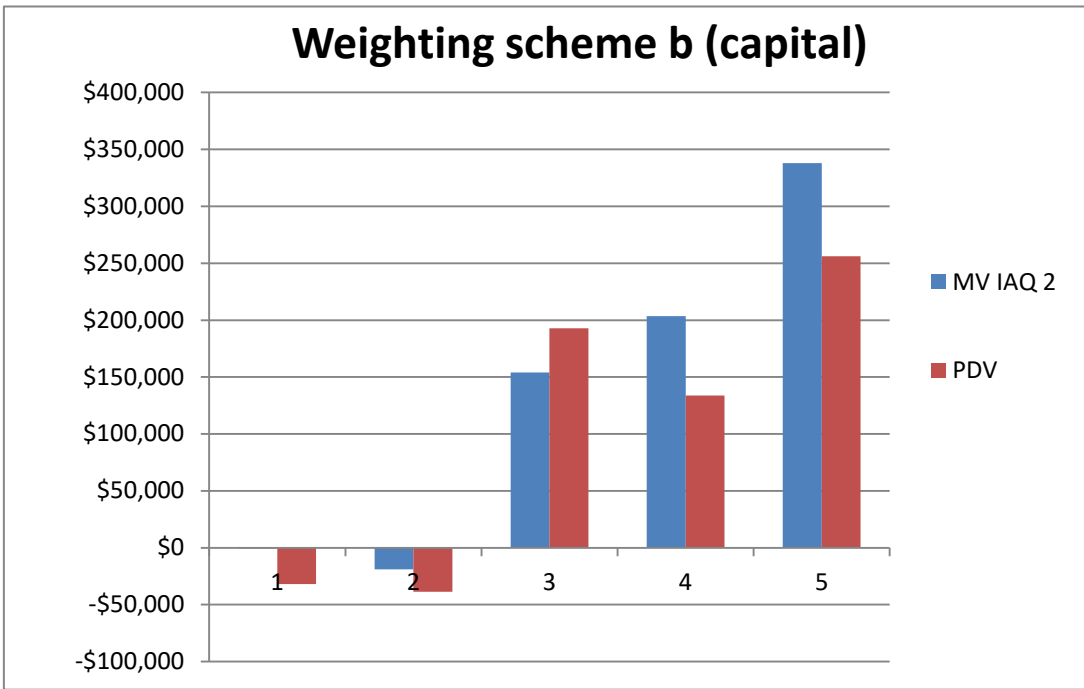


Figure 4.4 Weighting scheme b (capital): 1: Extra ACMV capital expenses; 2: Extra operational energy expenses; 3: Benefits of avoided sick leave; 4: Benefits of increased average mark; 5: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2: 18.3; (b) PDV: 4.6. All values are relative to the MV IAQ 1 scenario.

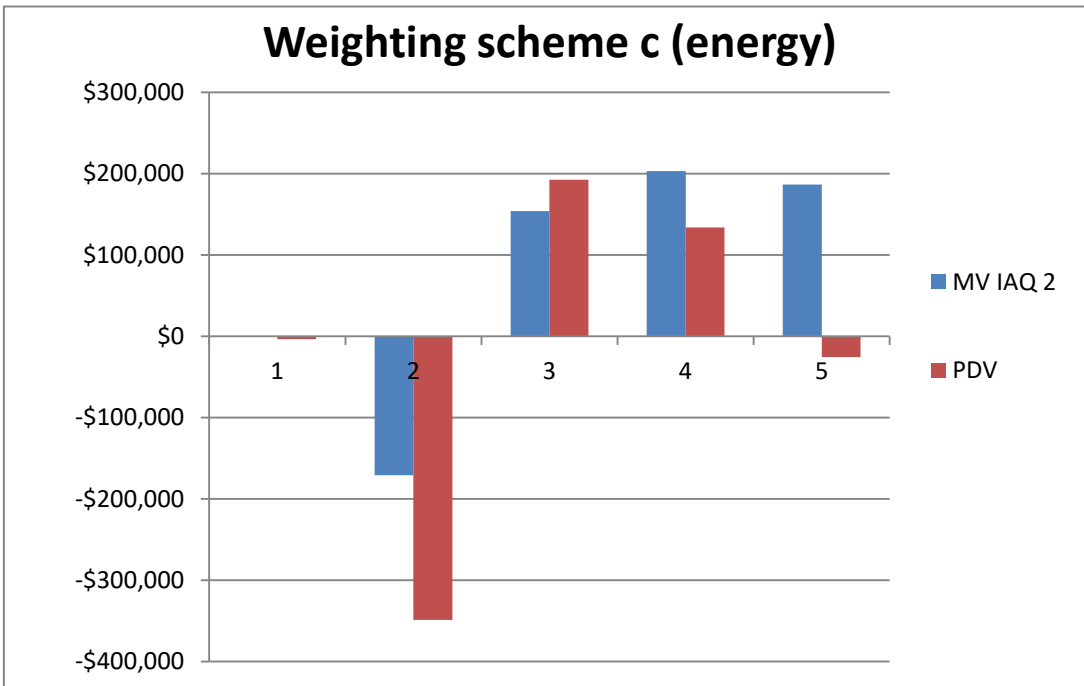


Figure 4.5 Weighting scheme c (energy): 1: Extra ACMV capital expenses; 2: Extra operational energy expenses; 3: Benefits of avoided sick leave; 4: Benefits of

increased average mark; 5: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2: 2.1; (b) PDV: 0.9. All values are relative to the MV IAQ 1 scenario. Higher percentage refers to better overall score.



Figure 4.6 Weighting scheme d (wellbeing): 1: Extra ACMV capital expenses; 2: Extra operational energy expenses; 3: Benefits of avoided sick leave; 4: Benefits of increased average mark; 5: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2: 83.5; (b) PDV: 44.2. All values are relative to the MV IAQ 1 scenario.



Figure 4.7 Weighting scheme e (performance): 1: Extra ACMV capital expenses; 2: Extra operational energy expenses; 3: Benefits of avoided sick leave; 4: Benefits of increased average mark; 5: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2: 104.2; (b) PDV: 33.1. All values are relative to the MV IAQ 1 scenario.

4.3.2. Sensitivity analysis

Sensitivity analysis is further conducted for the balanced scheme a. For each sensitivity analysis, only the benefits or extra expenses that would be influenced are plotted. The results are shown in Figures 4.8 to 4.14. As can be seen, the metrics are generally robust, as there are no abrupt changes when the individual metric varied within the range considered. The total net benefits are also significant and the variations of total net benefits among different metrics are also comparable.

The metric that causes the largest deviation of the benefits to extra expenses ratio is the energy tariff growth rate: 8.0 to 26.2 for MV IAQ 2 scenario, and 3.2 to 9.7 for PDV scenario. Deviations caused by varying other metrics are relatively less. Since the baseline values for the metrics were already conservatively estimated, in general

the two improved scenarios could still have good benefits to extra expenses ratio even under uncertainty.

For the interest rate, the benefits to extra expenses ratios have very little deviations from the baseline. This suggests that the monetary values in the future have very little impact on the ratio, as both the benefits and extra energy expenses are discounted by the same proportion. Nonetheless, the total net benefit is less under the high interest rate case, because the benefits are much more than the extra expenses, and therefore the absolute value reduction of benefits is larger when all the values are discounted by the same proportion.

For the room service life, the range of benefits to extra expenses ratio is 11.8 to 20.6 for MV IAQ 2 scenario, and 4.7 to 7.6 for PDV scenario. The total net benefits are less when the room service life is shortened. This is again because the benefits are much more than the extra expenses, and therefore although both the expenses and the benefits are reduced when the room service life is shortened, the absolute value reduction of benefits is larger.

For the avoided sick leave days, increased average marks, year of salary and number of students, the overall range of benefits to extra expenses ratios is similar to that of the room service life metric. These four metrics are related to the students' wellbeing and performance only. The deviations of the total net benefit and the benefits to expenses ratio for avoided sick leave days metric are relatively smaller than those of increased average marks and year of salary. This is mainly due to the higher monetary value of performance than the monetary value of avoided sick leave days. The range of deviations for the number of students is similar to that of avoided sick leave days.

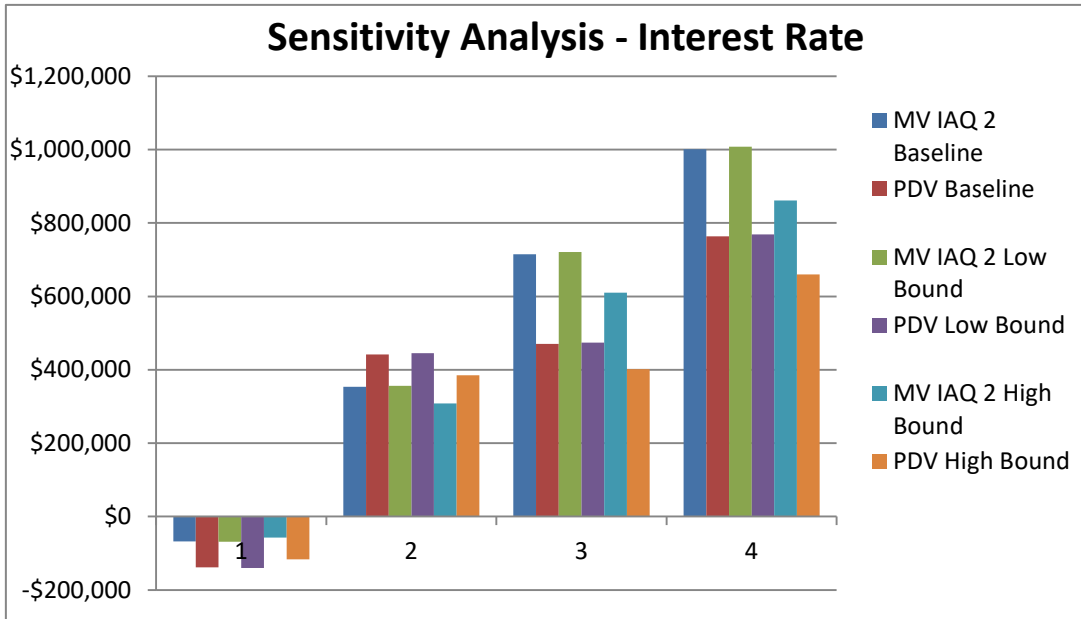


Figure 4.8 Sensitivity analysis for interest rate: 1: Extra operational energy expenses; 2: Benefits of avoided sick leave; 3: Benefits of increased average mark; 4: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 15.7; (b) PDV-Low Bound: 6.1; (c) MV IAQ 2-High Bound: 16.1; (d) PDV-High Bound: 6.2. All values are relative to the MV IAQ 1 scenario.

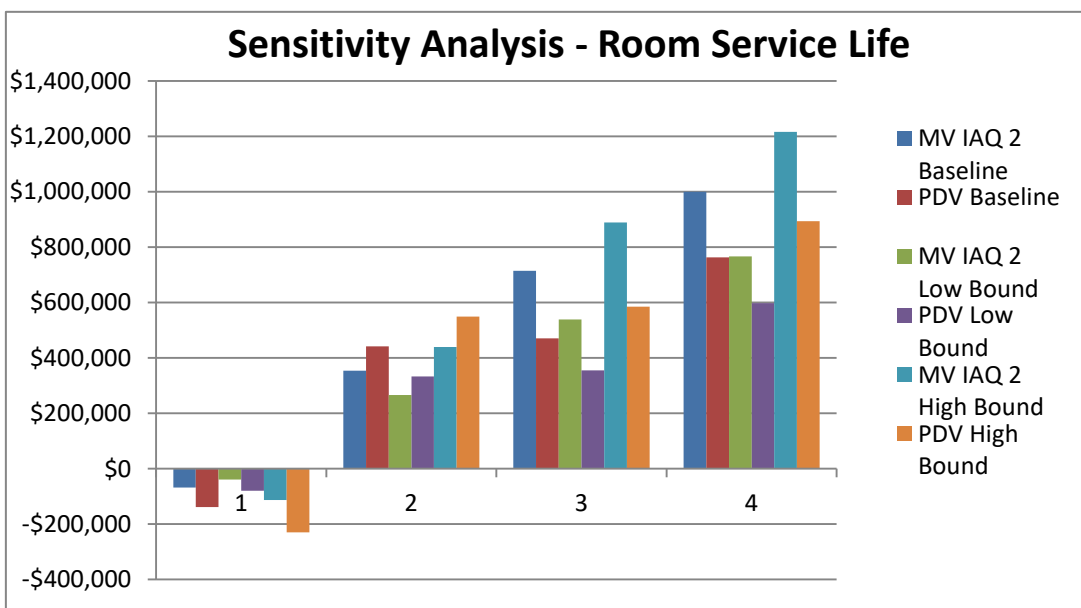


Figure 4.9 Sensitivity analysis for room service life: 1: Extra operational energy expenses; 2: Benefits of avoided sick leave; 3: Benefits of increased average mark; 4: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 20.6; (b) PDV-Low Bound: 7.6; (c) MV IAQ 2-High Bound: 11.8; (d) PDV-High Bound: 4.7. All values are relative to the MV IAQ 1 scenario.

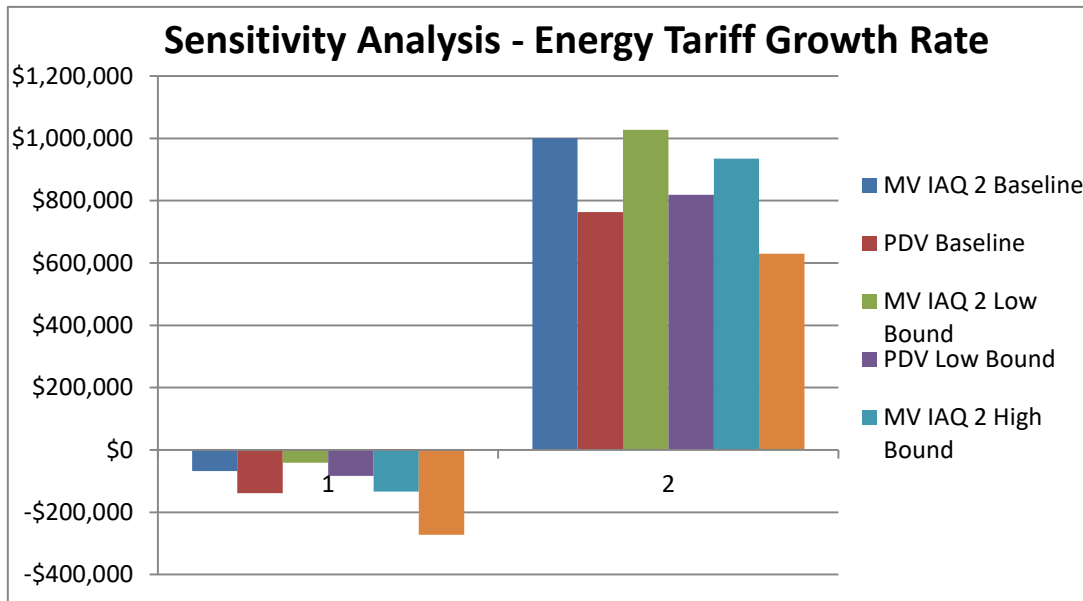


Figure 4.10 Sensitivity analysis for energy tariff growth rate: 1: Extra operational energy expenses; 2: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 26.2; (b) PDV-Low Bound: 9.7; (c) MV IAQ 2-High Bound: 8.0; (d) PDV-High Bound: 3.2. All values are relative to the MV IAQ 1 scenario.

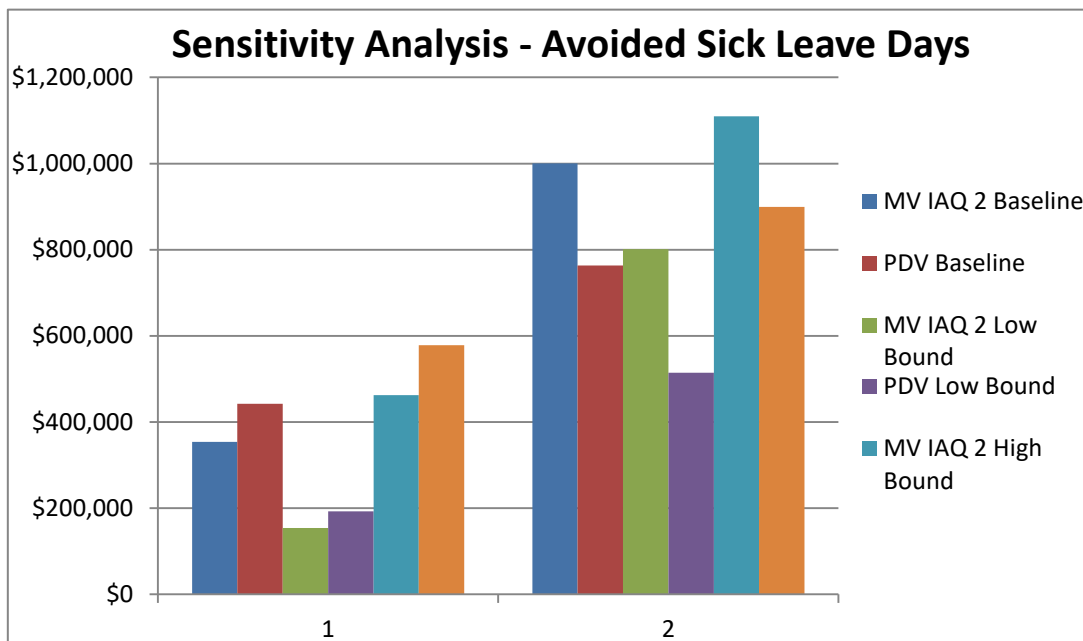


Figure 4.11 Sensitivity analysis for sick leave days: 1: Benefits of Avoided Sick Leave; 2: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 12.8; (b) PDV-Low Bound: 4.4; (c) MV IAQ 2-High Bound: 17.3; (d) PDV-High Bound: 7.0. All values are relative to the MV IAQ 1 scenario.

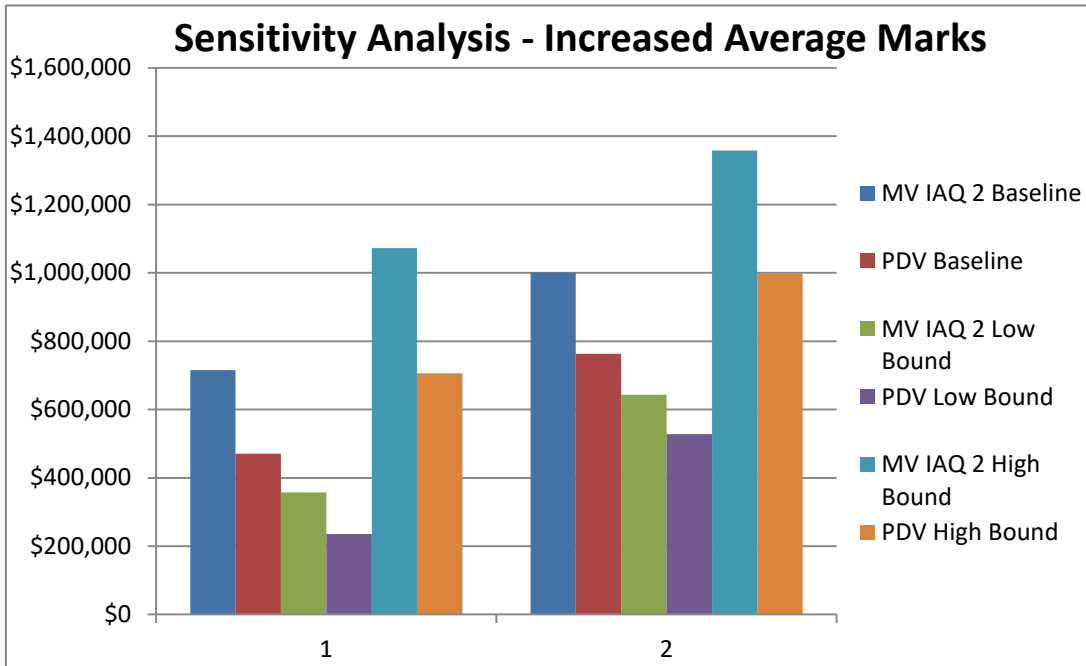


Figure 4.12 Sensitivity analysis for average marks: 1: Benefits of Increased Average Mark; 2: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 10.4; (b) PDV- Low Bound: 4.5; (c) MV IAQ 2-High Bound: 20.9; (d) PDV- High Bound: 7.7. All values are relative to the MV IAQ 1 scenario.

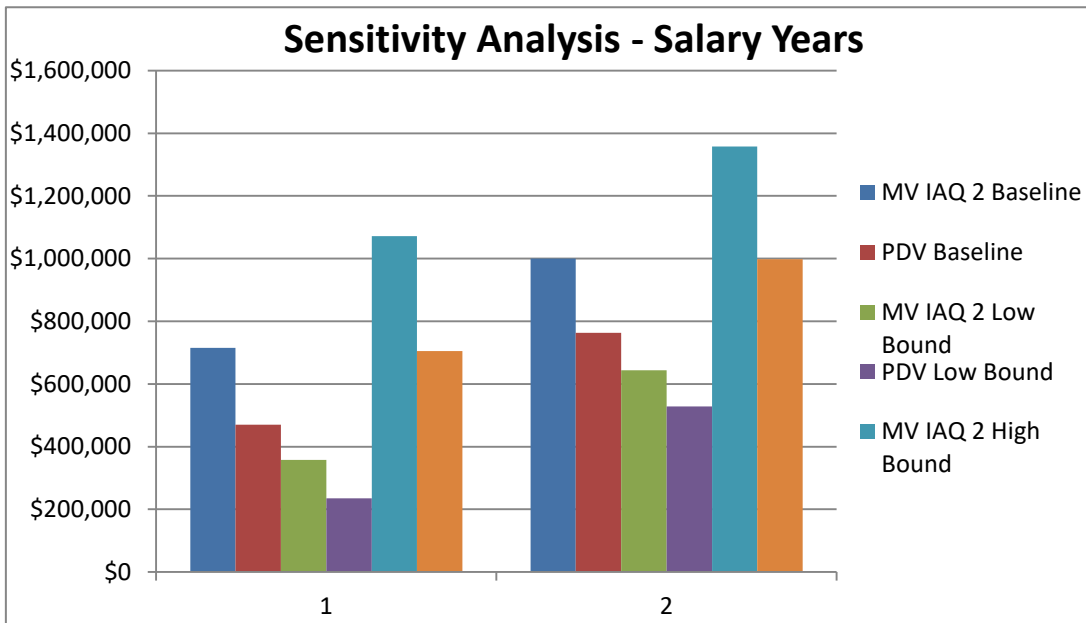


Figure 4.13 Sensitivity analysis for salary years: 1: Benefits of Increased Average Mark; 2: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2-Low Bound: 10.4; (b) PDV- Low Bound: 4.5; (c) MV IAQ 2-High Bound: 20.9; (d) PDV-High Bound: 7.6. All values are relative to the MV IAQ 1 scenario.

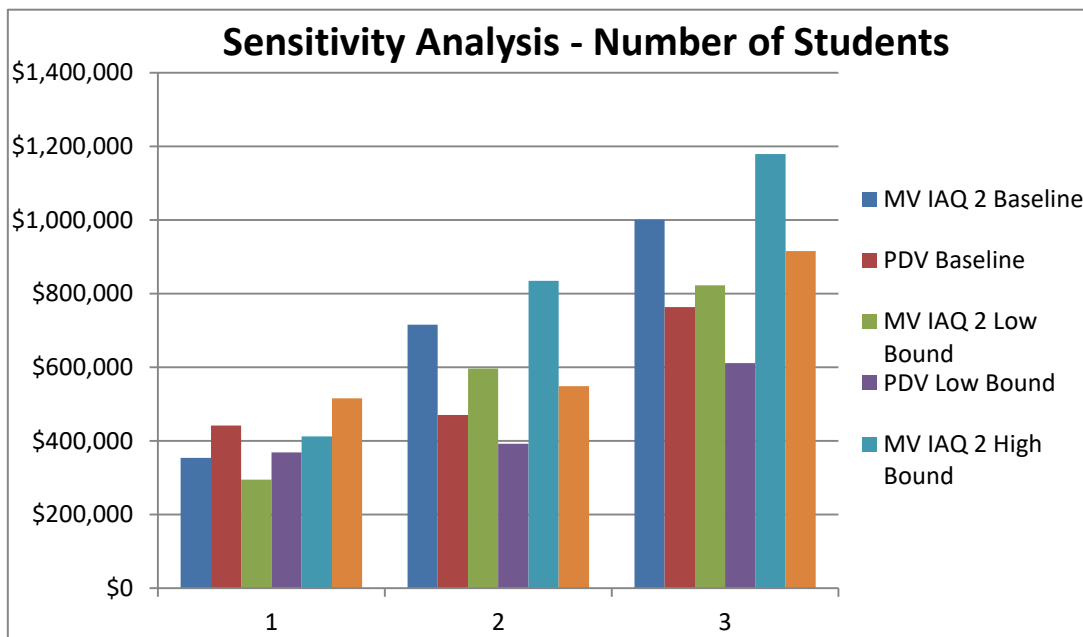


Figure 4.14 Sensitivity analysis for number of students: 1: Benefits of Avoided Sick Leave; 2: Benefits of Increased Average Mark; 3: Total net benefits. The Benefits to Extra Expenses Ratios: (a) MV IAQ 2- Low Bound: 13.1; (b) PDV- Low Bound: 5.1; (c) MV IAQ 2- High Bound: 18.3; (d) PDV-High v: 7.1. All values are relative to the MV IAQ 1 scenario.

4.4. Conclusions and outlook

In this study, the impacts of indoor environmental quality on students' wellbeing and performance in educational building were investigated with other major building metrics, with a case study of two university tutorial rooms. The metric for wellbeing of the students was the number of sick leave days, and the metric for performance was the weighted average marks. The monetized metrics for these two primary metrics were benefit of avoided sick leave and benefit of weighted average marks respectively. Different weighting schemes for the metrics were explored through LCC perspective. Sensitivity analysis was further conducted for the balanced weighting scheme. Main conclusions from this study include:

- For the baseline balanced weighting scheme a, the extra operational energy expenses are much more than the extra capital expenses. The PDV scenario

has more benefit of avoided sick leave, while the MV IAQ 2 scenario has more benefit of increased average mark. The MV IAQ 2 scenario also has more total net benefit. For the benefits to extra expenses ratios, the MV IAQ 2 scenario has a larger ratio than PDV scenario (15.7 as compared to 6.1), which is mainly due to the lower extra expenses in MV IAQ 2 scenario.

- For the weighting schemes b to e, the benefits to extra expenses ratios of scheme b (capital) are similar to those of balanced scheme a. For scheme c (energy), the net benefits of wellbeing and performance are almost negligible or even negative. For scheme d (wellbeing) and e (performance), higher weights for wellbeing and performance further increase the benefit to extra expenses ratios as compared with baseline balanced scheme a.
- For the sensitivity analysis of balanced weighting scheme, the metrics are generally robust, as there are no abrupt changes when the individual metric varies within the range considered. The total net benefits are also significant, and the variations of total net benefits among different metrics are also comparable. The metric that caused the largest deviation of the benefits to extra expenses ratio is the energy tariff growth rate: 8.0 to 26.2 for MV IAQ 2 scenario, and 3.2 to 9.7 for PDV scenario. For the interest rate, the benefits to extra expenses ratios have little deviations from the baseline. For the room service life, the range of benefits to extra expenses ratio is 11.8 to 20.6 for MV IAQ 2 scenario, and 4.7 to 7.6 for PDV scenario. For the avoided sick leave days, increased average marks, year of salary and number of students, the overall range of benefits to extra expenses ratios is similar to that of the room service life metric.

For a more sustainable building design and operation, balanced weighting scheme should be adopted, in contrary to the current practice where weights are heavily put on capital and energy while wellbeing and performance are often ignored. For the

baseline balanced scheme a, ratios are more comparable to the review studies for office buildings by Fisk, in which two examples of calculation with benefit-cost ratios of 9 and 14 were cited (Fisk 2001). The consideration of students' wellbeing and performance can lead to significant total net benefits for both the two improved scenarios, and the improvement carried out in the MV room has larger benefits to expenses ratio due to less extra expenses. The results emphasize the importance of considering students' wellbeing and performance into educational building design and operation, as the thermal or air quality conditions in school classrooms are often worse than the relevant stipulations in standards and building codes (Wargoeki et al. 2013). Investigations of other MV system rooms on the same campus of this study also revealed similar poor IAQ problems. The baseline values for different metrics are already conservatively estimated, so in general the two improved scenarios can still have good benefits to extra expenses ratio even under uncertainty. A further interesting point is the years of students' salary to be considered. For the baseline case, only the first year after graduation is considered, and the sensitivity analysis only varies in the range of ± 0.5 yr. As the student's starting salary normally has longer impact after graduation, incorporation of an extra 2 to 3 years' salary after graduation could lead to even more total net benefits.

Chapter 5 Human-building interaction under various indoor temperatures through EEG methods

5.1. Overview

This chapter explores the potential of EEG based methods for enhancing human-building interaction under various indoor temperatures. Correlations between EEG and subjective perceptions/tasks performance were experimentally investigated. Machine learning-based EEG pattern recognition was further studied. Utilization of the EEG frontal asymmetrical activities and the machine learning-based EEG pattern recognition method as a feedback mechanism of occupants, which can be implemented on a routine basis, has a great potential to enhance the human-building interaction in a more objective and holistic way.

5.2. Methodology

5.2.1. Experiment

The experiment was conducted in a typical office room in Nanyang Technological University, Singapore. The room is 4.7m in length, 3.1m in width, and 2.6m in height (floor to false ceiling). The air conditioning and mechanical ventilation (ACMV) system of the room is traditional mixing ventilation with cooling coil, and the room air temperature can be controlled by adjusting the valves of the ACMV. A heater was used to adjust the room air temperature. The effect of radiant temperature was considered minimal because the room is not exposed to sunlight and has no windows and no radiant asymmetry exists either. Therefore, operative temperature should equal to air temperature according to ASHRAE Standard 55 (ASHRAE Standard 55, 2013). Three room air temperature levels, i.e. 23, 26 and 29°C, were studied in this experiment and other environmental indices were kept relatively unchanged. The three temperature levels were designed to lead to equally spaced thermal sensations, centered at thermal neutral sensation based on typical

dressing code and indoor environment in Singapore's context. While it has been reported previously that occupants' performance is likely to increase towards the cooler conditions (e.g. 19 °C air temperature), indoor air temperature below 20 °C is less common in Singapore's context, and thus cooler conditions were not studied in the current work.

Twenty-two healthy university students (male-to-female ratio of 1.75) were recruited as human subjects. The human subjects were required to wear common local attire (short-sleeve shirt and trousers), which corresponds to a clothing level of 0.57clo according to the ASHRAE Standard 55. The experiment was within-subject and each human subject experienced all three temperature levels. Before the experiment, they were asked to keep good physical conditions. In each day, there were three timeslots, i.e. 10:30am-12:30pm, 1:00pm-3:00pm, and 3:30pm-5:30pm. Each human subject participated for three days, and could only choose the same timeslot in each day to minimize other confounding factors. To further ensure the data quality, only one human subject was tested in each timeslot.

Subjective questionnaires were used to investigate thermal comfort, perceptions of indoor environment, sick building syndrome (SBS), mood and self-perceived performance. Thermal comfort, perceptions of indoor environment and SBS were denoted as Questionnaire-I. Mood and self-perceived performance were denoted as Questionnaire-II. Computerized tasks were designed to evaluate performance, and measures were taken to minimize learning effect, including a) tasks were chosen such that they require very basic abilities; b) a practice session was conducted to help human subjects to be proficient with the tasks before the formal experiment, and c) three parallel sets of questions with similar difficulty but different contents were used in formal experiment. EEG was recorded both in rest condition (no tasks) and in task condition (doing computerized tasks). Body temperature was measured

twice in each timeslot. The sequence of temperature conditions among human subjects was also balanced to further minimize any sequential effects such as fatigue effects. The experimental procedure in each time slot is shown in Figure 5.1.

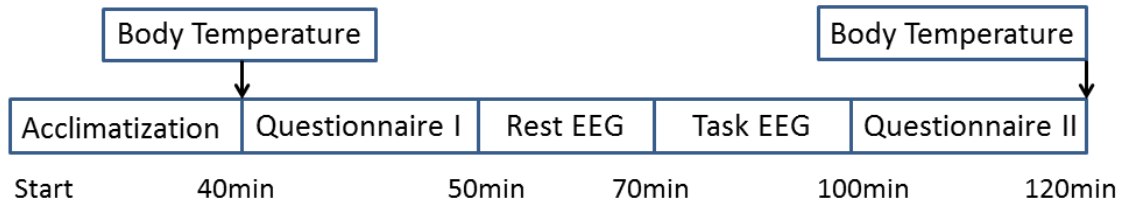


Figure 5.1 Procedure for each timeslot

5.2.2. Questionnaires, computerized tasks and body temperature data collection and analysis

The questionnaires and computerized tasks utilized were essentially the same as those used in Chapter 3. In particular, three tasks were adopted in this experiment:

- Short term memory: Two types of short term memory tests were used. Pair recall asked human subjects to remember two groups of character pairs each time followed by recalling the missing character in each pair (Kantowitz et al. 2009). Words recall asked subjects to remember two groups of words each time followed by recalling the words in each group (Solso et al. 2008).
- Perception: Visual trace asked human subjects to visually trace each curve and correctly label it (Yin et al. 2003).

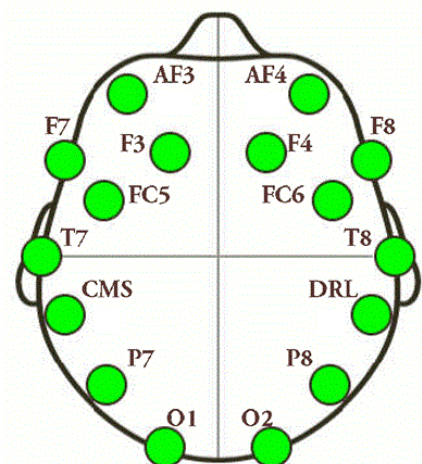
Body temperature was measured by a non-contact clinical thermometer (Visiofocus mod. 06400, TECNIMED SRL). Both the forehead temperature and the finger temperature were measured.

Non-parametric statistical tests were used for all the metrics for consistent comparisons, because distribution of many metrics didn't follow the normal distribution and cannot be tested by parametric statistical tests. Related-sample

Wilcoxon signed ranks test was used (within-subject). $P < 0.05$ was taken as significant level in the discussion unless stated otherwise, and p-value below significant level implies that significant difference exists and dominates the effect of random error.

5.2.3. EEG data collection and pre-processing

The device for EEG data collection is the Emotiv EPOC (EPOC+, Emotiv Inc. USA). The Emotiv EPOC is a high resolution, nonintrusive, and portable wireless headset that measures 14 channels of EEG data. The electrodes are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the International 10–20 system, forming 7 sets of symmetric channels as shown in Figures 5.2. Two extra electrodes (CMS/DRL) are used as references. The EPOC internally samples at the frequency of 2048 Hz, and then down-samples to 128 Hz per channel. The data are then sent to a computer via Bluetooth, which utilizes a proprietary USB dongle to communicate using the 2.4 GHz band. Prior to use, all felt pads on top of the sensors need to be moistened with saline solution. The Emotiv Software Development Kit (SDK) provides a packet count functionality to ensure no data is lost and real-time sensor contact display to ensure measurements quality. After the data collection, data were loaded to Matlab for further processing.



(a)

(b)

Figure 5.2 Emotiv EPOC: (a) setup; (b) channel locations

The EEG data were pre-processed by the widely used EEGLAB toolbox (version 13.4.4b) running under the Matlab environment (Delorme and Makeig 2004). The recommended pre-processing procedure by the EEGLAB developers was used in this study. The electrical noise (50/60Hz) was already removed inside the Emotiv EPOC headset. The continuous data imported into the EEGLAB toolbox were first high-passed at 3Hz to remove DC offset and low-frequency skin potential artifacts, and then low-passed at 45Hz to remove high-frequency noises. Non-stereotyped artifacts such as large movement noises were then visually rejected by scrolling the data. The remaining artifacts such as eye blinks and muscle activities were removed by the EEGLAB built-in independent component analysis (ICA) algorithm, which decomposes the EEG signal into maximally independent components and artifact components were then removed.

The artifacts-free continuous data were then segmented into 8-second epochs. Power spectrum analysis was conducted for each 8-second epoch by the EEGLAB's spectopo function, which uses the pwelch function from the Matlab signal processing toolbox. Each epoch was analyzed using a 128-point window with 64-point overlap, i.e. 50% overlap. This power spectrum analysis computed the discrete power densities within the range of 3-45Hz, which forms the basis for the subsequent analysis.

5.2.4. EEG frontal asymmetrical activities

The EEG metric used for establishing the correlations between EEG and subjective questionnaire-based results, and between EEG and objective task results is the brain asymmetrical activity. Brain asymmetrical activities have been widely studied by various brain measuring techniques including EEG and fMRI, and the results

indicated that the left-hemisphere of the brain is more correlated with positive/approach emotion, and the right-hemisphere of the brain is more correlated with negative/withdrawal emotion (Harmon-Jones 2003; Canli et al. 1998).

In this study, the frontal activities were quantified according to the previous literatures (Harmon-Jones 2003; Gola et al. 2003; MacLean et al. 2012) and the literature review in Chapter 2.3.3 as the mean power of beta range minus the mean power of alpha range, and higher value indicates more active. For a specific condition for each human subject, the mean power was calculated by averaging the power spectrums of data epochs. The frontal asymmetrical score was then calculated as the activity at F3 (left) minus F4 (right), and therefore higher asymmetrical score indicates more positive/approach emotion. Finally all human subjects' asymmetrical scores were averaged to give a final score for each specific thermal condition. Related-sample Wilcoxon signed ranks test was used (within-subject) for pairwise comparison.

5.2.5. Machine learning-based EEG pattern recognition

Linear discriminant analysis (LDA) classifier in Matlab statistics toolbox (Matlab R2013b) was used for the machine learning based EEG pattern recognition, and the detailed review can be found in Chapter 2.4. The selection of features, i.e. the multi-variables in the LDA, in the current work followed previous studies in EEG emotion recognition or mental vigilance recognition (Esfahani et al. 2011; Berka et al. 2004), where the mean power density in each 1Hz frequency range was used as the feature. Emotiv EPOC has 14 channels and 42 frequency ranges (within 3-45Hz range) were considered for each channel in this study. Therefore, the total number of features available was 588.

Individual-based user-dependent classifier, i.e. each human subject has his/her unique classifier, was used in this study. This approach was often used by studies in which the number of human subjects was relatively small (Esfahani et al. 2011; Picard et al. 2001; Healey et al. 1998), as EEG signal normally has large inter-person differences (Hamann & Canli 2004). On the other hand, user-independent classifier was explored by studies in which the number of human subjects was large, and inter-person differences were therefore able to be adjusted (Berka et al. 2004; Katsis et al. 2008; Kim et al. 2006).

The classification procedure was as follow: for each human subject, a) half of the data epochs were randomly selected to train the classifier, while the other half of the data epochs were kept for prediction; b) for the training data, the ANOVA was used to select the user-dependent features with the threshold of significance level $p < 0.05$, i.e. at least one thermal condition is significantly different for a feature to be selected; c) the LDA classifier was trained by the training data with the user-dependent features; and d) the trained LDA classifier was then used to classify the prediction data, and the classification rate was calculated as the percentage of correctly predicted data, i.e. the percentage of data epochs that were correctly predicted. As there are three thermal conditions, the classification rate needs to be sufficiently higher than $1/3$, i.e. the random rate of labeling the data correctly.

5.3. Results and discussion

5.3.1. Environmental background

Temperature, relative humidity (RH) and air velocity were continuously monitored by air velocity meters (Velocicalc air velocity meter 9545, TSI Inc.) during the experiment. CO₂ was continuously monitored by CO₂ meters (model CM-0018, CO₂ Meter, Inc. USA). All environmental data was collected at seating level in the vicinity of human subjects with a sampling rate of $1/60 \text{ s}^{-1}$, i.e. 1-min interval

(Table 5.1). As can be seen, the monitored temperatures in general were close to the targeted values.

Table 5.1 Environmental background in the vicinity of human subject

Targeted	23°C		26°C		29°C	
Monitored temperature and RH	Temp(°C)	RH(%)	Temp(°C)	RH(%)	Temp(°C)	RH(%)
	22.6±0.2	70.1±0.6	25.8±0.1	61.3±0.6	29.1±0.4	50.5±1.1
Monitored CO ₂ and air velocity: CO ₂ <1000ppm; Air-velocity<0.1m/s						

5.3.2. Subjective questionnaire

The results of the subjective questionnaire are shown in Table 5.2. For thermal sensation, 23°C condition led to slightly cool sensation, 26°C led to neutral sensation, and 29°C led to slightly warm sensation as defined by the 7-point scale, and the pairwise p-values were all significant. This was also in line with the prediction by ASHRAE standard 55. In the subsequent analysis, the three thermal conditions are denoted as cool, neutral and warm conditions respectively for convenience.

For thermal acceptability, all values were above neutral, which suggested that the three thermal conditions were deemed acceptable in general. Between neutral and warm conditions, neutral condition was considered more acceptable than warm condition, and the difference was significant. Between neutral and cool conditions, though the difference did not reach significance level, neutral condition still had higher value than cool condition, which suggested neutral condition was slightly more acceptable than cool condition. The p-value was not significant may be attributed to larger standard deviations. Between cool and warm condition, cool condition again had higher value, though the p-value was not significant possibly due to the same reason.

For breath sensation, all values were above neutral, which suggested that three conditions were generally deemed good. Cool condition led to the best sensation, neutral condition was in the middle, and warm condition was the worst. All pairwise p-values were significant. For air quality perception, the trend was similar to that of breath sensation, with the exception that the value of air quality perception under warm condition was below neutral, which suggested that warm condition was deemed as slightly unacceptable for air quality perception metric. Previous chamber studies and field investigations also suggested that in the range of acceptable thermal conditions, perceived air quality generally decreased as temperature increased (Seppanen et al. 1989; Mendell et al. 2002; Fang et al. 2004; Lan et al. 2011).

For general environment perception, the values were all above neutral. The values of cool condition and neutral condition were almost the same, which suggested that the general satisfaction for these two conditions were similar. The warm condition had lower value than other two conditions, which suggested that warm condition was relatively less satisfactory for this metric. The pairwise differences of cool-warm and neutral-warm were both significant. For mood and self-perceived performance, the trends were very similar to that of general environment perception, which suggested that human subjects' mood and self-perceived performance were most closely related to their perception of general environment.

Table 5.2 Results of questionnaire, computerized tasks and body temperature

Metrics		Cool	Cool-Warm P-value	Warm
Q1. Thermal sensation	Q1	3.09±1.02	<0.001	5.09±0.68
Q2. Thermal acceptability	Q2	4.64±1.34	0.126	4.14±1.21
Q3. Breath	Q3	6.43±0.84	0.001	5.14±1.70
Q4. Air quality	Q4	4.91±1.48	<0.001	2.91±1.02
Q5. General environment	Q5	5.27±1.28	0.002	4.32±1.25
Q6. Mood	Q6	5.59±1.10	0.009	4.79±1.27
Q7. Self-perceived	Q7	5.19±0.90	0.019	4.38±1.39

performance				
T1. Pair recall	T1	14.02±5.02	0.408	13.82±6.57
T2. Word recall	T2	6.45±2.11	0.527	6.86±2.07
T3. Visual trace	T3	27.23±7.80	0.983	27.82±7.29
B1. 40min-finger	B1	35.74±0.75	<0.001	36.54±0.64
B2. 40min-head	B2	36.73±0.38	0.039	37.00±0.44
B3. 120min-finger	B3	34.92±0.58	<0.001	36.34±0.64
B4. 120min-head	B4	36.59±0.28	<0.001	36.93±0.31
<p>Remarks: Q1-Q7, metrics of questionnaire: (1) Thermal Sensation: 1 refers to cold, and 7 refers to hot; (2) Thermal Acceptability, SBS, Environment, Mood and Self-perceived performance: 1 refers to very unacceptable/very bad, and 7 refers to very acceptable/very good.</p> <p>T1-T3, metrics of computerized tasks: (1) Pair Recall and Word Recall: accurate answers per minute; (2) Visual Trace: total accurate answers.</p> <p>B1-B4, body temperature in °C: (1) 40min-Finger and 40min-Head: measured at 40min for finger and forehead; (2) 120min-Finger and</p>		Cool-Neutral P-value	Neutral	Warm-Neutral P-value
	Q1	0.001	4.19±0.73	0.002
	Q2	0.296	5.09±1.44	0.023
	Q3	0.016	5.97±1.30	0.006
	Q4	0.026	4.00±1.69	0.001
	Q5	0.999	5.27±1.42	0.003
	Q6	0.138	5.51±1.22	0.010
	Q7	0.515	5.26±1.23	0.007
	T1	0.049	16.59±5.73	0.028
	T2	0.638	6.81±2.87	0.910
	T3	0.001	31.50±7.13	0.032
	B1	<0.001	36.56±0.59	0.781
	B2	0.121	36.85±0.39	0.106
	B3	<0.001	36.18±0.55	0.284
	B4	0.002	36.78±0.29	0.018

120min-Head: measured at the end of the session.				
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5.3.3. Computerized tasks

The results of the computerized tasks are summarized in Table 5.2 as well. For short-term memory tasks, values were accurate answers per minute (Glickman et al. 2005). For visual trace task which cannot be finished within given time, values represented total accurate answers. Because paired (within-subject) statistical test was used for performance analysis, variations of strategies among different human subjects to answer questions did not matter much.

Between cool and warm conditions, there were no significant differences for the three tasks. Between neutral and cool conditions, neutral condition led to better performance for two of the tasks than cool condition, and the differences were significant. Between neutral and warm conditions, neutral conditions again led to better performance for two of the tasks than warm condition, and the differences were significant. This trend was generally in accordance with previous studies. Seppanen et al. conducted a literature review, and summarized from various studies the performance decrements as a U-shape function of temperature, which showed that performance decrements were lowest around 24-26 degree (Seppanen et al. 2005).

5.3.4. Body temperature

The results of the body temperature are shown in Table 5.2. The body temperatures were closely related to the thermal sensation, i.e. lower body temperature leads to lower thermal sensation, and vice versa. The most reliable metric was the forehead temperature measured at the end of each timeslot, as all the pairwise p-values were significant. The main reason might be that forehead temperature is more stable than finger temperature, as human subjects may have different postures and therefore

finger temperature has larger standard deviation, which can be seen from the results. Measurements taken at the end was also more reliable than those taken immediately after the acclimatization period, as some of the p-values did not reach significance level for measurements taken at 40min. Body temperature could be used to correlated with thermal sensation, as previous researchers used finger skin temperature (Lan et al. 2011) or whole body weighted /unweighted skin temperature (Choi et al. 1997).

5.3.5. EEG frontal asymmetrical activities

The results of EEG frontal asymmetrical activities are shown in Figure 5.3. As asymmetrical scores were calculated as F3 (left) relative to F4 (right), F4 was the reference and therefore asymmetrical scores were plotted at F3 location.

For rest condition (i.e. not doing any tasks), the asymmetrical scores under cool and warm conditions were around (only minimally above) zero, which suggested that the emotion states under these two conditions did not show apparent positive/approach or negative/withdrawal emotion. For the neutral condition, the asymmetrical score was above zero, which suggested that the emotion state was positive/approach under this condition. The pairwise differences of neutral-cool and neutral-warm were both significant, while the pairwise difference of cool-warm was not significant. The questionnaire-I was an evaluation of the subjective perceptions under rest condition, and it can be seen that rest EEG frontal asymmetrical activities were more closely related to the thermal acceptability, as neutral condition was also subjectively perceived as better and more acceptable than the other two thermal conditions. Other metrics in questionnaire-I, such as perception of air quality or general environment, were not well related to the rest EEG frontal asymmetrical activities, because these subjective metrics indicated that cool condition led to better perception.

For task condition, the EEG frontal asymmetrical activities were similar to those under rest condition. The questionnaire-II was an evaluation of mood and self-perceived performance immediately after the computerized tasks, and it can be seen that the task EEG frontal asymmetrical activities were less related to these two metrics, as these two metrics did not show significant difference between cool and neutral conditions. Rather, the task EEG frontal asymmetrical activities related more closely with the actual performance of computerized tasks, as both the asymmetrical scores under task condition and the performance of computerized tasks indicated that the neutral condition led to the best state, while the other two thermal conditions were similar and led to relatively worse states. This further indicated that self-perceived performance does not necessarily relate to actual performance.

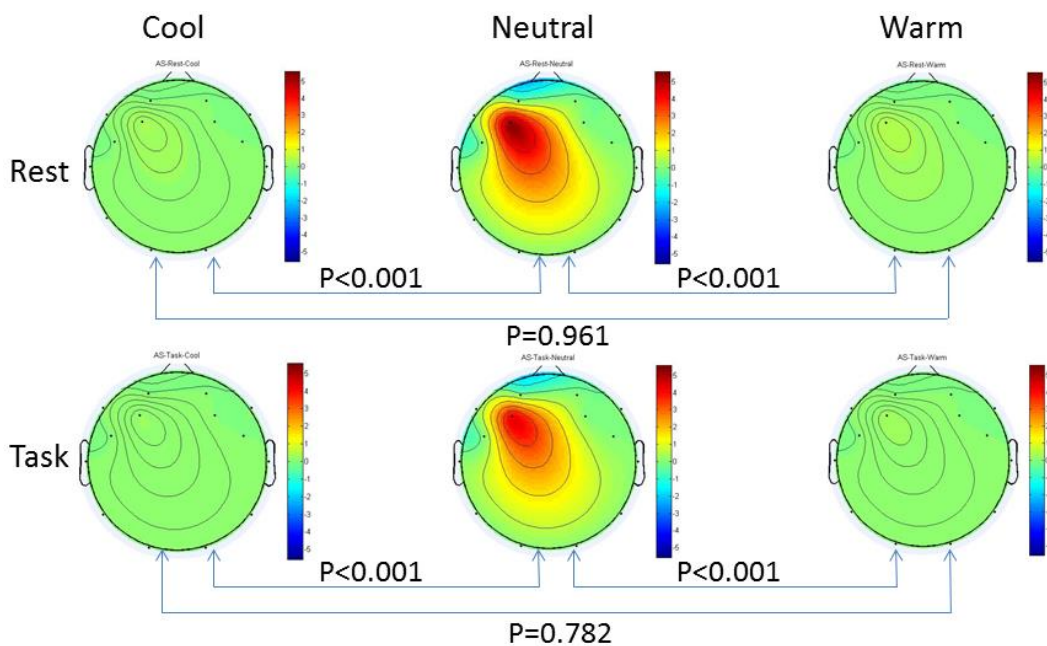


Figure 5.3 EEG frontal asymmetrical activities: the asymmetrical scores were plotted at F3 location on a scale of -5 to 5.

5.3.6. Machine learning-based EEG pattern recognition

The machine learning-based EEG pattern recognition results for the rest condition and task condition are shown in Figure 5.4. The full-set features varied from person to person and were in the range of 400-500. For each human subject, the classification rate of full-set features was first calculated, and then the full-set features were reduced one by one and the corresponding classification rates were calculated. Finally the rates were averaged across human subjects that led to the curves in Figure 5.4. The standard deviation bars denote the dispersion among human subjects, and were plotted at 20-feature intervals. The random rate of 1/3 was assigned to classifiers with zero feature case. In addition, detailed classification results for each human subject can be found in Figures A.1 and A.2 in Appendix A, and each line represents one human subject.

As can be seen for rest and task conditions, the classifiers with full-set features led to the best average classification rates of above 95%. For the rest condition, the average classification rate went below 90% and began to diverge significantly after around 200 features, and reached its first low point at around 100 features. The rest average classification rate then increased again until around 50 features, and finally decreased again. For the task condition, the general pattern was similar with slightly different turning points. The task average classification rate reached its first low point at around 150 features, and this low point was higher than that of rest condition. The task average classification rate then increased again until around 80 features, and this peak was flatter and higher than that of rest condition. Finally the task average classification rate decreased again. The results suggested that the LDA classifiers can well classify the different mental states under three thermal conditions for both rest and task conditions in roughly two feature ranges. The first range was from the full-set features to around 200 features, and the second range was around 50-80 features. The classification rates in the first range were higher

than that in the second range. Still, for the LDA classifiers, more features did not necessarily guarantee higher classification rate, as there was a low point between these two ranges.

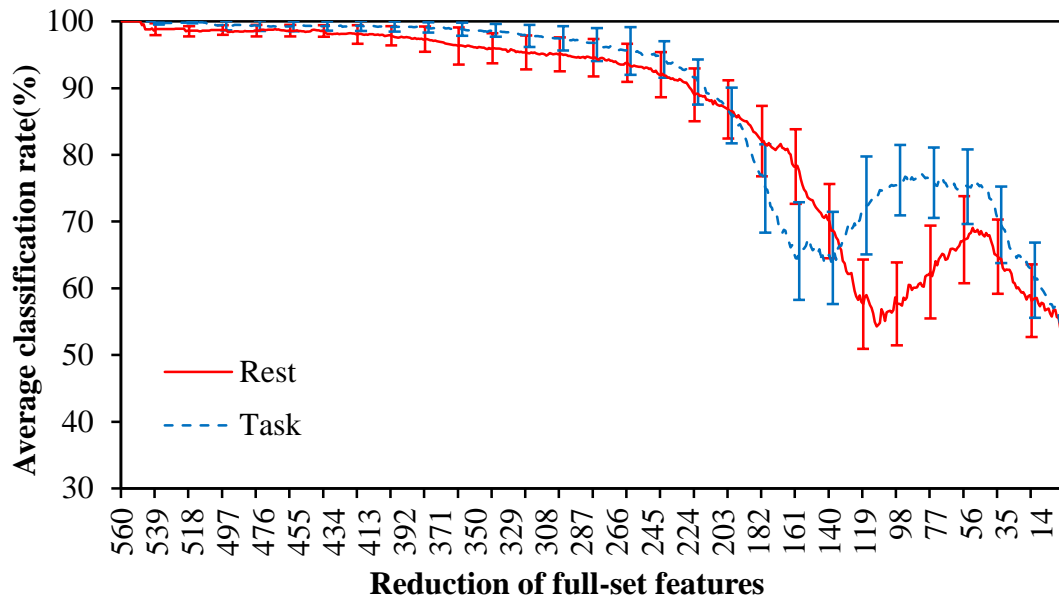


Figure 5.4 Machine learning based EEG pattern recognition. For the full-set features averaged across human subjects: a) rest: the average number is 494, and the average classification rate is 98%; b) task: the average number is 489, and the average classification rate is 99%.

5.4. Conclusions and outlook

In this study, new EEG-based methods to enhance human-building interaction under various indoor temperatures were experimentally investigated. Correlations between EEG and subjective perceptions, and between EEG and tasks performance were established by the EEG asymmetrical frontal activities. Machine learning based EEG pattern recognition was further explored. Main conclusions from this study include:

- The three temperature levels led to three distinct thermal sensations, which were also closely related to forehead skin temperatures. For the thermal acceptability metric, neutral condition was deemed as the most acceptable. For the breath sensation and perceived air quality, cool condition led to the

best sensation, neutral condition was in the middle, and warm condition was the worst. For the general environment perception, mood and self-perceived performance, cool condition and neutral condition were similar, while warm condition was deemed as relatively less satisfactory.

- For the computerized tasks, neutral condition led to the best performance than the other two thermal conditions. Cool and warm conditions led to similar task performance.
- For the EEG frontal asymmetrical activity, trends of rest condition and task condition were similar: neutral thermal condition led to more positive/approach emotion than the other two thermal conditions, while the other two thermal conditions were similar. The EEG rest frontal asymmetrical activity was more related to the thermal acceptability metric in the subjective questionnaire. The EEG task frontal asymmetrical activity also related well to the computerized tasks performance.
- For the machine learning based EEG pattern recognition, full set of user-dependent features rates were the best for both the rest and task conditions (above 95%). The LDA classifiers can well classify the different mental states under three thermal conditions for both rest and task conditions in roughly two feature ranges.

The EEG asymmetrical activities can be used as a more objective metric to corroborate traditional subjective questionnaire-based methods and task-based methods, and as a useful input to improve the human-building interaction. Furthermore, the machine learning based EEG pattern recognition method can be utilized to classify different mental states under various thermal conditions in a more automatic and efficient way for human-building interaction. The current study focused on the user-dependent classifiers, which can achieve very high accuracy as a result of not considering inter-person differences. This approach requires that each

individual has to train his/her own classifier, which can then be incorporated into different buildings where each individual normally stays. The potential future study is to build a more general user-independent classifier with a much larger population by considering main differences in gender, age, personality, occupation, etc., as some of the researchers have already explored in emotion or mental vigilance EEG studies (Berka et al. 2004; Katsis et al. 2008; Kim et al. 2006). Although the classification accuracy might be compromised by using the user-independent classifier, this can make the technique more applicable since it does not require training individual classifiers. Furthermore, as larger sample size can improve the statistical power, more human subjects in future study may also reveal other useful findings. In addition, the tasks and settings in environmental chambers could be quite different from those in actual offices. In future studies other more complicated tasks such as decision makings (Satish et al. 2012) and longer exposure similar to those in actual offices could also be explored. In future experiments, it would also be interesting to explore the lower range of temperature. In general, the use of EEG indices and machine learning based EEG pattern recognition techniques can help to improve the two-way dynamic human-building interaction in the future.

Chapter 6 Machine learning-based EEG pattern recognition for human-building interaction under various indoor temperatures

6.1. Overview

This chapter focuses on machine learning-based EEG pattern recognition methods, which also form the main feedback mechanism in the human-building interaction. The data to explore these methods are processed EEG data in Chapter 5. Specifically, the performance of classifying different mental states under various temperatures was compared among various machine learning methods, and these further demonstrated the suitability of machine learning methods in the context of indoor thermal environment. Three classifiers as reviewed in Chapter 2.4 were used for machine learning-based EEG pattern recognition methods, i.e. linear discriminant analysis (LDA), Naive Bayes (NB), and K-nearest neighbor (KNN). Moreover, linear continuous features of mental states under various temperatures were found and checked by interpolation and extrapolation, which can be a potential way to establish more classes without conducting more experiments.

6.2. Methodology

6.2.1. Method to compare different classifiers' performance

The performance of LDA, NB and KNN classifiers were compared. The procedure to calculate classification rate was as follows: for each human subject, a) half of the data epochs were randomly selected to train the classifier, while the other half of the data epochs were kept for prediction; b) for the training data, the ANOVA was used to select the user-dependent features with the threshold of significance level $p < 0.05$, i.e. at least one thermal condition is significantly different for a feature to be selected; c) the classifier was trained by the training data with the user-dependent features; and d) the trained classifier was then used to classify the prediction data, and the classification rate was calculated as the percentage of correctly predicted

data. The classification rates of different classifiers were calculated by this procedure and then then compared.

6.2.2. Method to find linear continuous features for class interpolation

A potential way to interpolate different classes is to interpolate the features. In this study, linear continuous features were searched, which can be used for further class interpolation. The method to find linear continuous features was as follows: for each individual feature of each human subject, a) the mean value of data epochs at cool condition and the mean value of data epochs at warm condition were used to construct a line; b) the mean value of neutral condition was interpolated from this line, and normal distribution random values were generated by using this interpolated mean value and the interpolated standard deviation. Three cases of interpolated standard deviation were considered: mean, minimum, and maximum of cool condition and warm condition; c) a LDA classifier was trained by the experimental data at cool and warm conditions and interpolated data at neutral condition; d) the experimental data at neutral condition were then classified by this LDA classifier, and the classification rate was calculated as the percentage of correctly predicted data. Finally if this classification rate passed a satisfactory threshold, then this feature was deemed as linear continuous.

It should be noted that higher classification rate indicates that the absolute value of the line's slope should be large enough (i.e. the mean values under the three thermal conditions should be different enough), and the standard deviations should be small enough. In addition, after the linear continuous features were found, these features would also be tested for extrapolation cases. Two cases were tested: extrapolated cool condition and extrapolated warm condition. The procedures were similar to that of interpolation.

6.3. Results and discussion

6.3.1. Performance of different classifiers

The averaged results of LDA, NB and KNN classifiers are shown in Figure 6.1 for the rest condition and in Figure 6.2 for the task condition. The average number of full-set features among human subjects was 494 for the rest condition and was 489 for the task condition. The average number of training samples was 36 for rest condition and 50 for task condition. For each case (e.g. LDA classifier rest condition): a) each human subject's full-set features classification rate was calculated; b) then the full-set features were reduced one by one and the corresponding classification rates were calculated; c) finally the rates were averaged across human subjects. The random rate of 1/3 was assigned to the final zero feature cases. For each case the standard deviations among human subjects were also plotted onto the secondary vertical axis. In addition, detailed classification results for each human subject are shown in Figures A.1 to A.6 in Appendix A, and each line represents one human subject.

For the LDA classifier, the full-set features classification rates were 98% for the rest condition and 99% for the task condition. For the rest condition, the average classification rate dropped below 90% at around 200 features, and reached its first low point at around 100 features. The rest average classification rate then increased again until around 40-50 features, and finally decreased again. For the task condition, the general pattern was similar with slightly different turning points. The task average classification rate reached its first low point at around 150 features, and then increased again until around 50-80 features, and finally decreased again. The results suggested that the LDA classifier can well classify the different mental states under three thermal conditions for both rest and task conditions in roughly two feature ranges, and the classification rates in the first range were higher than that in the second range. The results also suggested that for the LDA classifiers,

more features did not necessarily guarantee higher classification rate, as there was low point between these two ranges. The main reason behind the low points should be under-sampling of training data coupled with inter-dependence of features. Theoretically the classification errors should decrease with increasing number of features, but this may not be true in practice because the number of training samples is often much less than the number of features, known as under-sampling problem. Some researchers have put forward methods to select optimal number of features as a function of sample size for different classification methods (Hua et al. 2005), or put forward feature reduction methods such as uncorrelated LDA to cope with potential under-sampling problems that could arise (Ye et al. 2004). Still, the results in Figures 6.1 and 6.2 showed that as long as the number of features was in the two ranges, i.e. either sufficiently large or close to the number of training samples, the classification rates were generally satisfactory.

For the NB classifier, the full-set features classification rates were 93% for the rest condition and 97% for the task condition. As these full-set features rates were lower than those of the LDA classifier, this suggested that the features were not entirely independent, and therefore for full-set features the covariance approach of LDA was more appropriate than the NB's approach of independent feature treatment. Unlike the LDA classifier, the decreasing pattern of NB classifier was monotonic for both the rest and task conditions. Again, since the main difference between LDA and NB classifiers in this study is their treatments of inter-dependent characteristics of features, the pattern difference between LDA and NB classifiers further showed that the non-monotonic decreasing behavior of LDA classifier should be caused by the feature inter-dependence characteristics coupled with under-sampling problem. For the features decreasing pattern of NB classifier, the classification rate dropped below 90% at around 270 features for the rest condition and at around 170 features for the task condition, and the task condition had better classification performance

than the rest condition through the feature reduction process. For both the rest and task conditions, the NB classifier had lower classification rates and larger standard deviations among human subjects than the LDA classifier in the range between full-set features to the vicinity of LDA classifier’s low point.

For the KNN classifier, the full-set features classification rates were 91% for the rest condition and 93% for the task condition. The classification rate dropped below 90% at around 450 features for the rest condition and at around 350 features for the task condition. The decreasing pattern was also monotonic. For both the rest and task conditions, the KNN classifier had lower classification rates than the NB classifier through the feature reduction process. This suggested that the probability-based approach is more appropriate than the simple geometric distance-based approach. The standard deviations among human subjects were similar for both the KNN and NB classifiers.

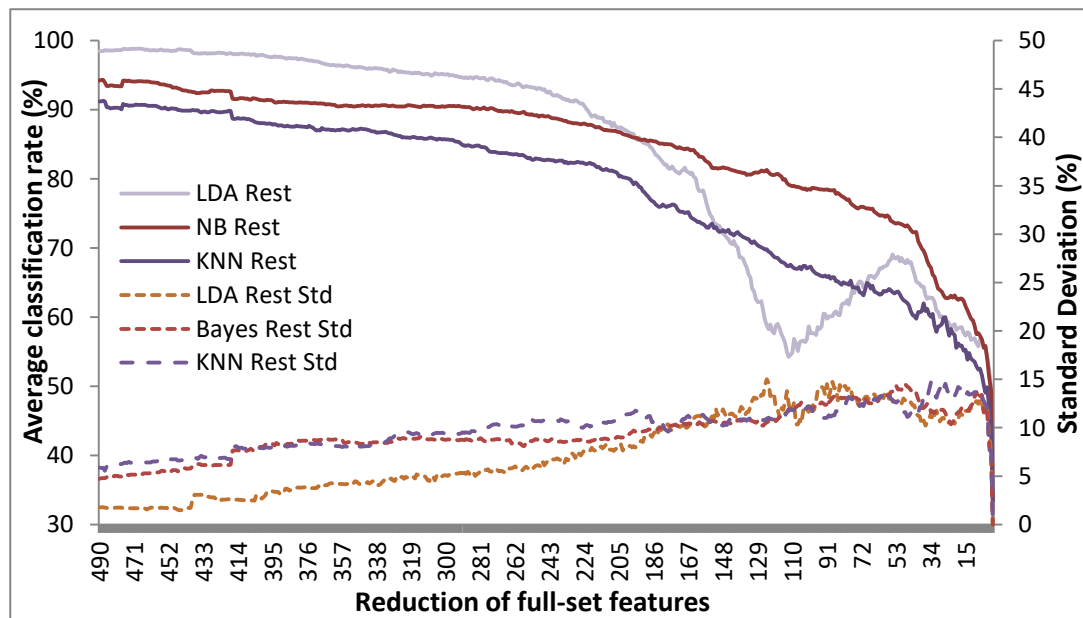


Figure 6.1 Comparison of different classifiers for rest condition: summary. Classification rate averaged across human subjects for full-set features: a) LDA rest: 98%; b) NB rest: 92%; c) KNN rest: 89%.

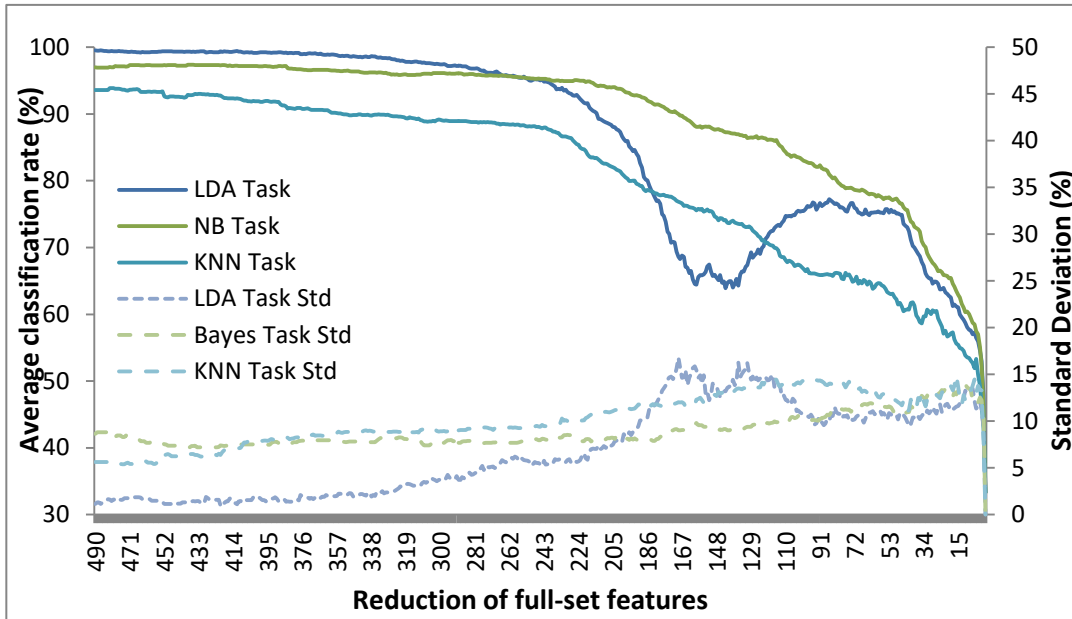


Figure 6.2 Comparison of different classifiers for task condition: summary. Classification rate averaged across human subjects for full-set features: a) LDA task: 99%; b) NB task: 97%; c) KNN task: 92%.

6.3.2. Linear continuous features for class interpolation

The results of interpolation for rest condition and task condition are shown in Figures 6.3 and 6.4 respectively. Three cases of standard deviations were used for interpolation: the mean, maximum and minimum standard deviations of cold condition and warm condition. These three cases give the possible range of interpolated standard deviation, and are denoted as “Meanstd”, “Maxstd” and “Minstd”. The horizontal axis is the selection threshold, meaning that a particular feature will be considered as linear continuous only if its classification performance passes a threshold. In this study the selection threshold ranged from random rate (i.e. 33%) to 80%. The left vertical axis denotes the average classification rate of features that pass a selection threshold, and the right vertical axis denotes the average number of these features. All these average values were across human subjects. The error bars denote the deviations across human subjects, and were plotted for the “MeanStd” case only, as the three standard deviation cases were similar.

As can be seen, for both the rest and task conditions, the average number of features passing 33% threshold was around 60-70, and the average classification rate of these features was around 60%. Higher selection threshold led to less selected features but better average performance of these features, i.e. higher average classification rates. For instance, for both the rest and task conditions, the average number of features passing 67% threshold was 20-30 and the average classification rate of these features was around 80 %. The number and the average classification rates of linear continuous features were not very sensitive to the way of interpolating standard deviations, as “Meanstd”, “Maxstd” and “Minstd” cases were very close. For the average classification rates of the selected features, the deviations among human subjects (i.e. the error bars) decreased with higher selection threshold for both the rest and task conditions. For the number of the selected features, the deviations among human subjects did not decrease significantly with higher selection threshold for the rest condition, but decreased significantly for the task condition. The features that did not pass the pre-defined threshold may have large standard deviations or less mean value differences among three temperature conditions. As the range of temperature conditions was quite large in this study, linear interpolation may perform even better in narrower temperature intervals, i.e. more linear continuous features could be found with higher average classification rates.

The extrapolation performance of these selected linear continuous features was further calculated and is shown in Figure 6.5. The suffix “Warm” or “Cold” means that this particular thermal condition was extrapolated. Only “Meanstd” cases were calculated, as the previous interpolation results already showed that three standard deviation interpolation methods were similar. The error bars again denote the deviations across human subjects and were plotted at sparser intervals. As can be seen, the classification rates were in the 10-40 % range, which was close to the 33 %

random rate and therefore not viable. The deviations among human subjects were not sensitive to selection threshold. The results suggested that for interpolation the linear continuous features may perform relatively well, but they may not necessarily perform well for extrapolation. This may be due to the reason that the selected features were not perfectly linear, and therefore extrapolation would magnify the errors estimated by the linear line, especially for the large range of temperature conditions in this study. This also suggested that interpolation is more reliable.

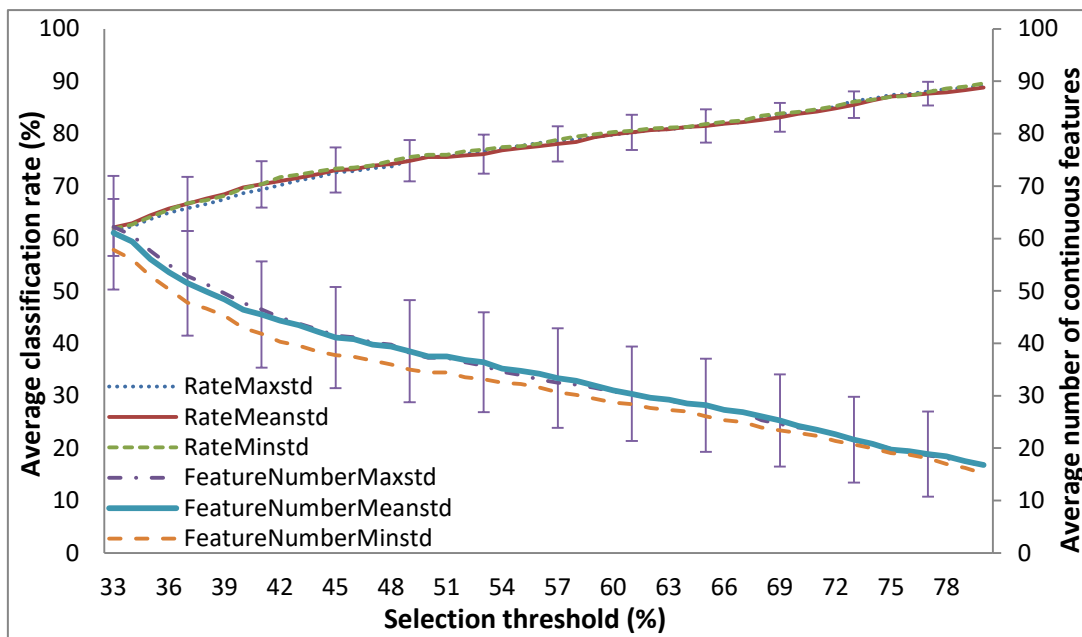


Figure 6.3 Rest condition interpolations. Each line denotes the average values across all human subjects. The error bars denote the standard deviations across all human subjects, and are plotted for the “Meanstd” case only.

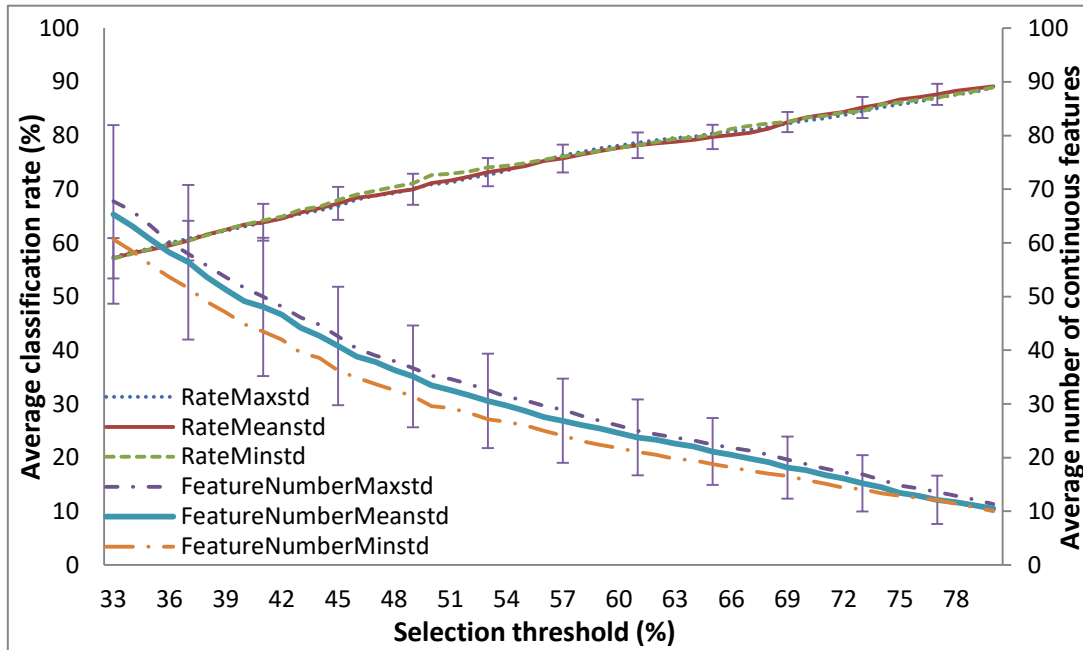


Figure 6.4 Task condition interpolations. Each line denotes the average values across all human subjects. The error bars denote the standard deviations across all human subjects, and are plotted for the “Meanstd” case only.

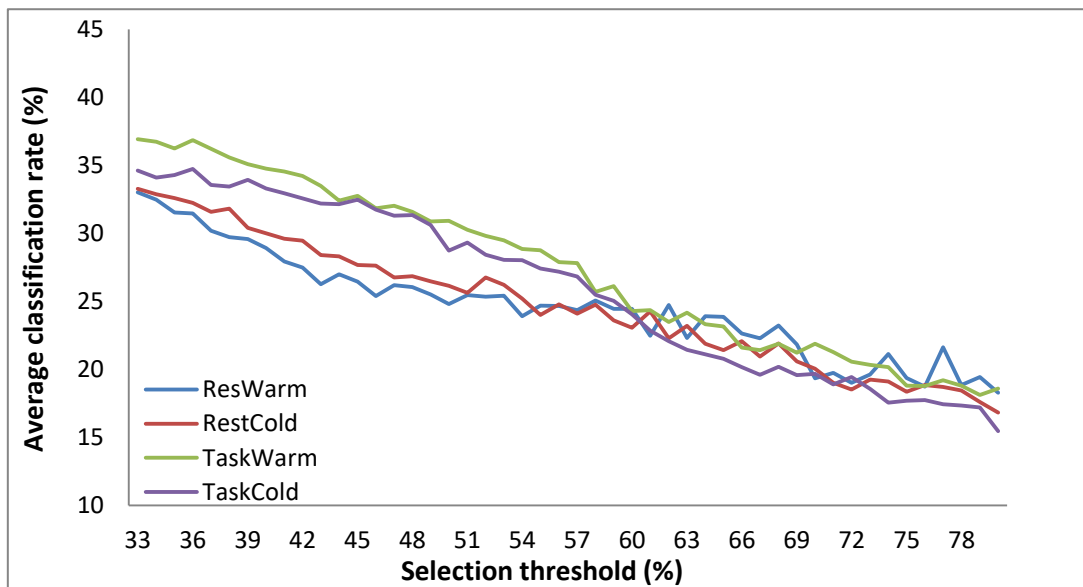


Figure 6.5 Rest and task conditions extrapolation of “Meanstd” case. Each line denotes the average classification rates across all human subjects. The suffix “Warm” or “Cold” means that this particular thermal condition was extrapolated.

6.4. Conclusions and outlook

In this study, machine learning-based EEG pattern recognition methods under different indoor temperatures were illustrated with an experiment. The suitability of machine learning methods in the context of indoor thermal environment was explored, and the performance of different classifiers was compared. The method to select linear continuous features for class interpolation was also explored. Main conclusions from this study include:

- For the full-set features, the performances of different classifiers were satisfactory. The LDA classifier had better performance (approaching 100%) than the NB classifier (93% for rest and 97% for task). The KNN classifier (91% for rest and 93% for task) performed slightly worse than the NB classifier. In general the machine learning methods were suitable in the indoor thermal environment context.
- The patterns of cumulative reduction of features were different among classifiers. The LDA classifier had low point at around 100-150 features, while the NB and KNN classifiers decreased monotonically. From the full-set features to the location of LDA classifier's low point, the LDA classifier had the highest classification rate, and the NB classifier was intermediate, and the KNN classifier was the worst. In this range, LDA classifier also had the smallest standard deviations among human subjects, while the NB and KNN classifiers had similarly larger standard deviations.
- The linear continuous features were selected by interpolation method. For both the rest and task conditions, the average number of features passing 33% threshold was around 60-70, and the average classification rate of these features was around 60%. Higher selection threshold led to less selected features but higher average performance of these features, i.e. higher average classification rates. The numbers and the average classification rates

of linear continuous features were not very sensitive to the way of interpolating standard deviations.

- The linear continuous features were also checked by extrapolation, and the classification rates mainly concentrated in the 10-40% range, which was close to the 33% random rate and therefore not viable.

The linear interpolation method provides a way to interpolate data that are not experimentally available. This method should work even better in narrower temperature intervals, which could be achieved with more experimental thermal conditions. This study main focused on applying machine learning-based EEG methods in the indoor thermal environment. In the potential future studies, these methods can also be applied to other aspects of indoor environment, such as indoor air quality environment. As already discussed in Chapter 4.4, the current study adopted user-dependent classifiers. The potential future study is to build a more general user-independent classifier by adjusting main differences inter-person differences. In general, the use of machine learning-based EEG pattern recognition methods can help to improve the two-way dynamic human-building interaction in a more automatic and efficient way in the future.

Chapter 7 Human-building interaction under different indoor air quality through EEG methods

7.1. Overview

This chapter investigates the potential of EEG-based methods to improve human-building interaction under different indoor air quality (with two outdoor air supply rates of 3.5 and 11L/s-person). Correlations between EEG and subjective perception/task performance were studied through experiment. Machine learning-based EEG pattern recognition was further investigated. In general, utilization of the EEG theta and alpha bands and the machine learning based EEG pattern recognition method as a feedback mechanism can help to enhance the human-building interaction in a more objective way.

7.2. Methodology

7.2.1. Experiment

The experiment was conducted in a normally furnished office room in Nanyang Technological University, Singapore. The room is 4.7 m in length, 3.1 m in width, and 2.6 m in height (floor to false ceiling). The air conditioning and mechanical ventilation (ACMV) system of the room is traditional mixing ventilation with cooling coil, and the outdoor air supply rate can be controlled by adjusting the valves of the ACMV and sealing some of the ACMV inlets. Two outdoor air supply rates, i.e. 3.5 and 11 L/s-person were studied in this experiment. The lower value was chosen to be slightly above the minimum rate of 2.5 L/s-person for office space as recommended by the ASHRAE Standard 62.1 (ASHRAE Standard 62.1-2010).

Twenty-five healthy university students were recruited as human subjects. The experiment was within-subject and each human subject experienced all two ventilation conditions. Before the experiment, they were asked to keep good

physical conditions. There were three timeslots in each day: 10:30am-12:30pm, 1:00pm-3:00pm, and 3:30pm-5:30pm. Each human subject participated for two days, and could only choose the same timeslot in each day to minimize other confounding factors. To further ensure the data quality, only one human subject was tested in each timeslot. The human subjects were unaware of the intervention and were told to keep thermally neutral by adjusting clothing.

Subjective questionnaires were designed to investigate general perceptions of indoor environment, sick building syndrome (SBS), mood and self-perceived performance. Perceptions of indoor environment and SBS were denoted as Questionnaire-I. Mood and self-perceived performance were denoted as Questionnaire-II. Computerized tasks were also designed to evaluate performance, and measures were adopted to minimize learning effect, including a) the chosen tasks require very basics abilities; b) a practice session before the formal experiment was conducted to help human subjects to be proficient with the tasks, and c) two parallel sets of tasks with similar difficulty but different contents were used in formal experiment. EEG was recorded both in rest condition (no tasks) and in task condition (completing computerized tasks). The sequence of ventilation conditions among human subjects was also balanced to further minimize any sequential effects such as fatigue effects. The experimental procedure in each time slot is shown in Figure 7.1.

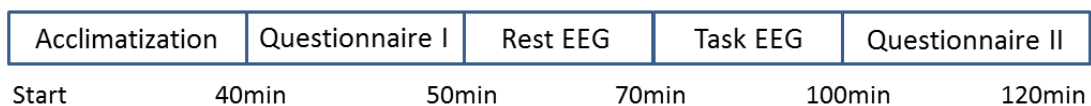


Figure 7.1 Procedure for each timeslot

7.2.2. Subjective questionnaires and computerized tasks data collection and analysis

The questionnaires and computerized tasks utilized were essentially the same as those used in Chapter 3. In particular, five tasks were adopted in this experiment:

- Short term memory: Two types of short term memory tests were used. Pair recall asked human subjects to remember two groups of character pairs each time followed by recalling the missing character in each pair (Kantowitz et al. 2009). Words recall asked subjects to remember two groups of words each time followed by recalling the words in each group (Solso et al. 2008).
- Reaction time: This test asked human subjects to type the character shown on the screen as fast as possible to evaluate the reaction time (Lezak et al. 2004).
- Perception: Two types of perception tests were selected. Visual trace asked human subjects to visually trace each curve and correctly label it (Yin et al. 2003). Stroop test asked human subjects to judge whether the meaning of the words correspond to their actual color as shown (Solso et al. 2008).

Non-parametric statistical tests were used for all the metrics for consistent comparisons, because the distribution of some metrics didn't follow the normal distribution and therefore cannot be tested by parametric statistical tests. Related-sample Wilcoxon signed ranks test was used (within-subject). $P < 0.05$ was taken as significant level in the discussion unless stated otherwise, and p-value below significant level means that significant difference exists and dominates the effect of random error.

7.2.3. EEG data collection and analysis

The EEG data collection and preprocessing methods were identical as those in Chapter 5. The site preparation is shown in Figure 7.2.

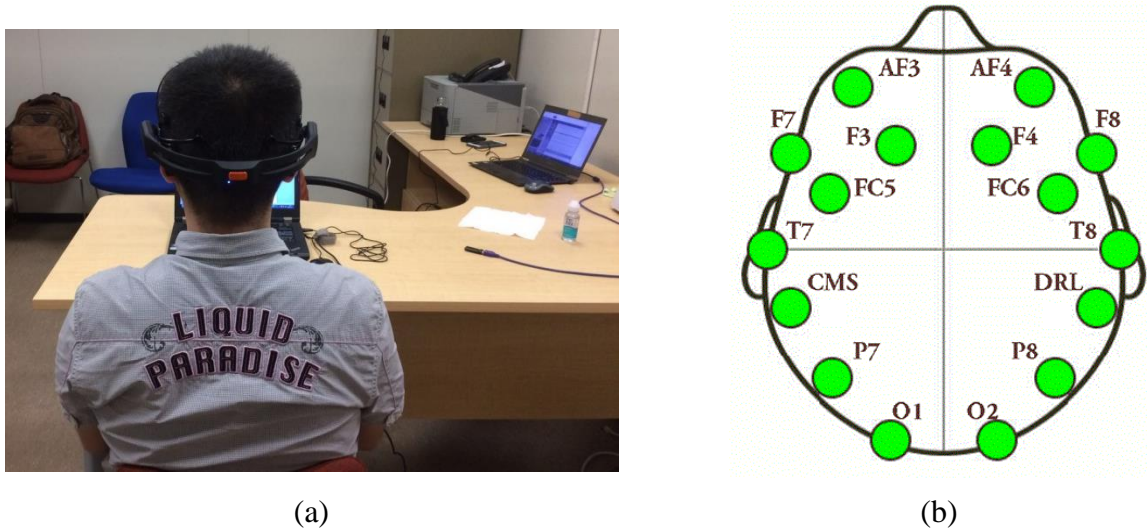


Figure 7.2 Emotiv EPOC: (a) setup; (b) channel locations

The EEG metrics used for establishing the correlations between EEG and subjective questionnaire-based results, and between EEG and objective task results are the power densities of different frequency bands, which were reviewed in Chapter 2.3.3. In this chapter, the mean power of theta wave and the mean power of alpha wave were used to study the mental states. For theta wave higher value therefore indicates relatively more drowsiness, and for alpha wave higher value indicates relatively less attention/concentration. For a specific condition for each human subject, the mean power was calculated by averaging the power spectrums of data epochs. Then all human subjects' values were averaged to give a final value for each specific condition. Related-sample Wilcoxon signed ranks test was used (within-subject) for pairwise comparison.

For the machine learning based EEG methods, two types of classifiers were explored: the linear discriminant analysis (LDA) and the support vector machine

(SVM). The detailed review can be found in Chapter 2.4. The protocol for the selection of features, the type of classifiers, and the classification procedure were the same as those in Chapter 5.

7.3. Results and discussion

7.3.1. Environmental background

The air-exchange rates (AERs) were measured by the CO₂ decay method using CO₂ meters (model AZ-0003, CO₂ Meter Inc. USA). The outdoor air supply rates were then normalized from the AERs. CO₂, air temperature and relative humidity (RH) were continuously monitored by CO₂ meters during the experiment. Air velocity was measured by an air velocity meter (Velocicalc air velocity meter 9545, TSI Inc.). All environmental data was collected at seating level in the vicinity of human subjects with a sampling rate of 1/60 s⁻¹, i.e. 1-min interval (Table 7.1). As can be seen, the monitored outdoor air supply rates were close to the targeted values, and CO₂ level decreased as ventilation rate increased. Other environmental parameters were generally the same between the two ventilation conditions. The accuracy of CO₂ measurement was $\pm 40\text{ppm} \pm 3\%$ of measured value. The accuracy of temperature measurement was $\pm 0.6^\circ\text{C}$. The accuracy of relative humidity was $\pm 5\%$ RH. These small uncertainties were not expected to affect human responses.

Table 7.1 Environmental background in the vicinity of human subject

	Outdoor Air Supply Rate (L/s-person)			Outdoor Air Supply Rate (L/s-person)		
Targeted	3.5			11		
Monitored	3.8±0.1			11.1±0.7		
	AER(/h): 0.72±0.02			AER(/h): 2.11±0.13		
	CO ₂ (ppm)	Temp (°C)	RH (%)	CO ₂ (ppm)	Temp (°C)	RH (%)
	1244±70	24.4±0.1	62.2±0.4	618±45	24.1±0.1	58.9±0.6
Air-velocity < 0.1 m/s						

7.3.2. Subjective questionnaire

The results of the subjective questionnaire are shown in Table 7.2, and only the subjective metrics that reach significance level $p < 0.1$ were listed. As can be seen, low ventilation led to more preference for air movement than high ventilation, and the difference was significant. This could be caused by the perception that the air was more stuffy and stagnant under low ventilation condition. For the breath sensation, all values were above neutral, which suggested that the two conditions were generally deemed good. Nonetheless, the low ventilation condition still led to worse breath sensation as compared with high ventilation. For the eye sensation, the values were above neutral, and low ventilation condition also led to worse perception. The increase of SBS as a result of poorer air quality and higher CO₂ level caused by low ventilation were generally in accordance with previous studies (Seppanen et al. 1999; Wargocki et al. 2000; Tham 2004). For the mood and self-perceived performance, the values were all above neutral. The low ventilation condition again led to worse perception. The p-values for these two metrics did not reach $p < 0.05$ level, but were still below 0.1. In general, the questionnaire results suggested that the low ventilation condition could lead to relatively worse subjective perceptions than the high ventilation condition.

Table 7.2 Results of questionnaire and tasks. (1) Q1-Q5, metrics of questionnaire: Preference for air movement: scale 1 refers to prefer more air movement, and scale 7 refers to prefer less; SBS, Mood and Self-perceived performance: scale 1 refers to very bad/unacceptable, and scale 7 refers to very good/acceptable. (2) T1-T5, metrics of computerized tasks: values are accurate answers per minute (short-term memory tasks) or total accurate answers (other tasks).

Metrics	Low Ventilation	High Ventilation	P-value
Q1. Preference for air movement	3.59±0.85	4.23±0.92	0.004
Q2. Breath sensation	5.51±1.47	5.93±1.24	0.048
Q3. Eye sensation	5.45±1.28	5.85±1.09	0.054
Q4. Mood	5.05±1.33	5.44±1.07	0.085
Q5. Self-performance	4.60±1.21	5.17±1.13	0.069

T1. Pair recall	12.71±5.13	15.57±5.57	0.033
T2. Stroop	46.82±7.80	48.61±7.41	0.041
T3. Visual trace	5.30±1.63	5.82±1.57	0.067
T4. Reaction time	198.09±34.13	202.09±33.59	0.210
T5. Word recall	6.89±2.59	6.86±2.33	0.832

7.3.3. Computerized tasks

The results of the computerized tasks are summarized in Table 7.2. For short-term memory tasks, values were accurate answers per minute (Glickman et al. 2005). For other tasks that cannot be finished within the given time, values represented total accurate answers. As paired (within-subject) statistical test was used for performance analysis, variations of strategies among different human subjects to answer questions did not matter much.

As can be seen, for T1-T3 tasks, low ventilation condition led to worse performance than high ventilation condition. For pair-recall task and stroop task, the p-values were below 0.05, and for visual trace task, the p-value was slightly above 0.05 but still below 0.1. For reaction time task, the low ventilation condition again led to worse performance, though the p-value did not reach significance level, possibly due to the large standard deviations. For the word-recall task, the two conditions did not show difference. Previous studies also showed that when the air quality was worse as a result of low ventilation rate, the work performance would deteriorate (Wargocki et al. 2002; Wargocki et al. 2004; Wyon 2004; Wargocki & Wyon 2007). Furthermore, CO₂ alone could also lead to work performance deterioration as demonstrated by Satish et al., though at higher level of 2,500 ppm with outdoor air supply rate kept constant at all times around 25 L/s-person (Satish et al. 2012). In general, the overall trend of the computerized tasks indicated that the low ventilation rate could lead to worse task performance, which could be caused by

poorer air quality, higher CO₂ level, and the accompanied worse subjective perceptions.

7.3.4. EEG frequency bands

For the rest condition (i.e. not doing any tasks), only the theta waves were found different between the two ventilation conditions. For the task condition, only the alpha waves were found different between the two ventilation conditions. These results are plotted in Figure 7.3.

For the rest condition, the theta waves were found different at FC6 and F8 locations, where the values were both higher under low ventilation condition than those under high ventilation condition. This indicated that low ventilation condition could lead to relatively more drowsiness in rest condition. As the questionnaire-I was an evaluation of the subjective perceptions under rest condition, the higher theta activities could also be related with the relatively more preference for air movement and more SBS under low ventilation condition.

For the task condition, the alpha waves were found different at P8 location, where the value was higher under low ventilation condition than that under high ventilation condition. This indicated that the low ventilation condition could lead to less attention/concentration for task completion. This was also related with the performance of the computerized tasks, as the low ventilation condition led to relatively worse performance for the majority of computerized tasks, which could be the results of less attention/concentration as shown by the higher alpha value. The questionnaire-II was an evaluation of mood and self-perceived performance for the completion of the computerized tasks, and the relatively worse perception under low ventilation condition might also be related with the higher alpha activities.

As can be seen for rest and task conditions, the indoor air quality can affect brain activity as measured by EEG. EEG not only can explain and correlate to the results of traditional questionnaire-based method and task-based method, but also provides a more objective and potentially more sensitive way to evaluate the impact of indoor air quality on human.

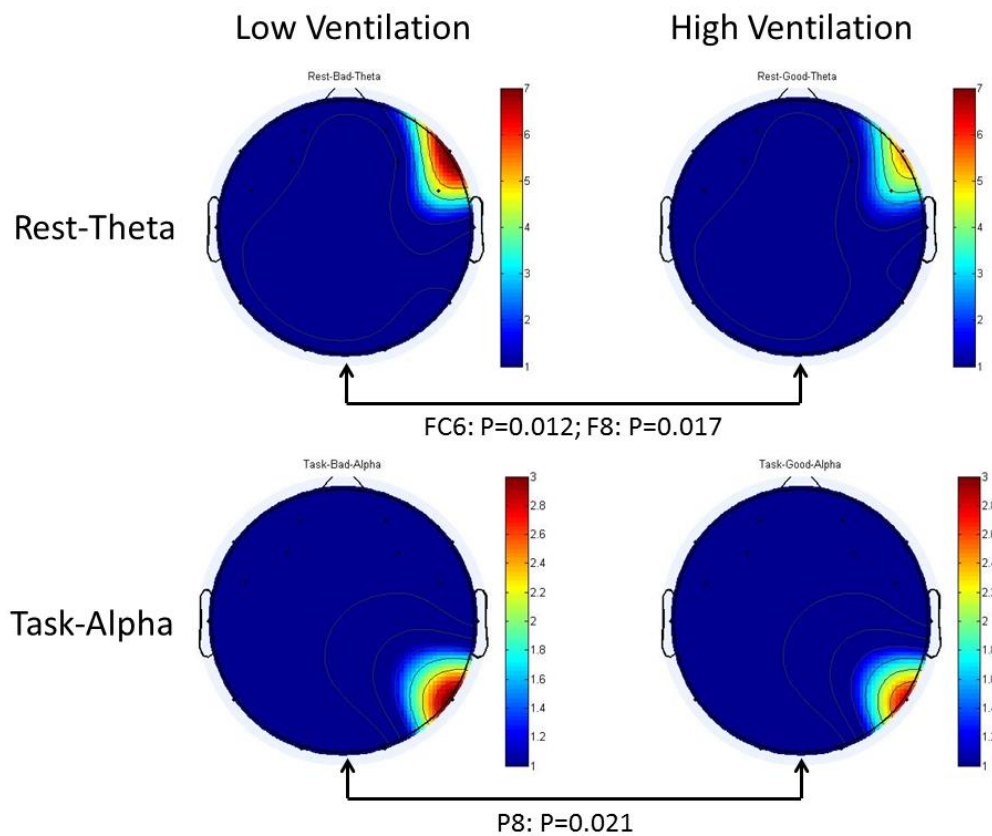


Figure 7.3 EEG frequency bands: (1) Rest condition: theta waves were found different at FC6 and F8 locations, drawn on a scale of 1-7; (2) Task condition: alpha waves were found different at P8 location, drawn on a scale of 1-3.

7.3.5. Machine learning based EEG pattern recognition

The averaged results of machine learning-based EEG pattern recognition for the LDA and SVM classifiers are shown in Figure 7.4. Each classifier was applied to both the rest and task conditions. For each case (e.g. LDA classifier rest condition): a) each human subject's full-set features classification rate was first calculated; b)

then the full-set features were reduced one by one and the corresponding classification rates were calculated; c) finally the rates were averaged across human subjects. The random rate of 1/2 was assigned to classifiers with zero feature case. For each case the standard deviations among human subjects were also plotted onto the secondary vertical axis. In addition, detailed classification results for each human subject are shown in Figures A.7 to A.10 in Appendix A, and each line represents one human subject.

As can be seen for the LDA classifier, full-set features led to the best classification rates of above 95% for both rest and task conditions. For the rest condition, the classification rate went below 90% at around 140 features, and reached its first low point at around 80 features. The classification rate then increased again until around 50 features, and finally decreased again. For the task condition, the general pattern was similar with slightly different turning points: the classification rate went below 90% at around 170 features, and reached its first low point at around 100 features. The results suggested that the LDA classifiers can well classify the different mental states under two indoor air quality conditions for both rest and task conditions in roughly two feature ranges. The first range was from the full-set features to around 140-170 features, and the second range was in the vicinity around 50 features. The classification rates in the first range were higher than those in the second range. Still, for the LDA classifier, more features did not necessarily guarantee higher classification rate, as there was a low between these two ranges. The standard deviations among human subjects for both rest and task conditions were similar and increased monotonically with reduction of features.

For the SVM classifier, full-set features again led to the best classification rates of above 95% for both rest and task conditions. For both the rest and task conditions, the classification rate went below 90% at around 70 features. Unlike LDA classifier,

the decreasing pattern of SVM classifier was monotonic. The results suggested that the SVM classifier can well classify the different mental states in the range from full-set features to around 70 features. For the SVM classifier, the standard deviations among human subjects for both rest and task conditions were similar and again increased monotonically with reduction of features. The SVM classifier had smaller standard deviations than LDA classifier in the range where LDA classifier had low point.

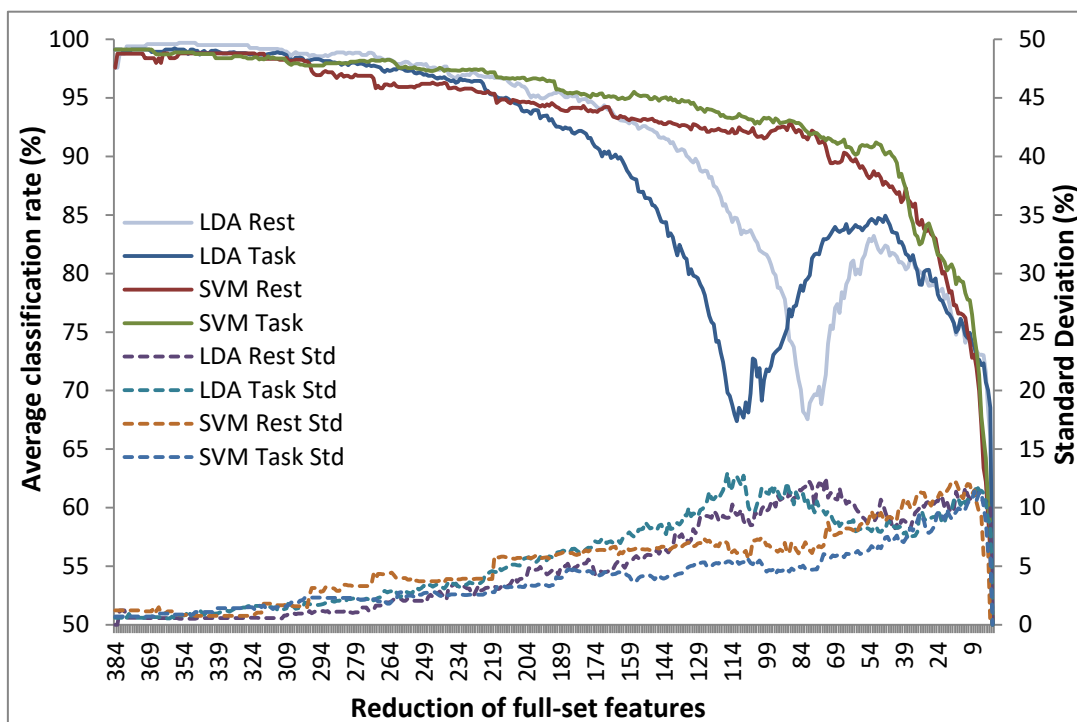


Figure 7.4 Machine learning based EEG pattern recognition. For the full-set features averaged across human subjects: a) LDA rest: 97%; b) LDA task: 96%; c) SVM rest: 95%; d) SVM task: 97%.

7.4. Conclusions and outlook

In this study, EEG-based methods to enhance human-building interaction under various indoor air quality environments were illustrated by an experiment with two different ventilation rates. Correlations between EEG and subjective perceptions, and between EEG and tasks performance were established by the EEG frequency

bands. Machine learning based EEG pattern recognition was further demonstrated.

Main conclusions from this study include:

- For the subjective questionnaire, low ventilation led to more preference for air movement, which could be caused by the perception that the air was more stagnant. For the breath sensation and eye sensation, all values were above neutral, which suggested that the two ventilation conditions were generally deemed good. Nonetheless, for both two metrics the low ventilation condition still led to relatively worse perception, which could be a result of poorer air quality and higher CO₂ level.
- For the computerized tasks, the overall trend of the computerized tasks indicated that the low ventilation rate could lead to relatively worse task performance, which could be caused by poorer air quality, higher CO₂ level, and the accompanied worse subjective perceptions.
- For EEG rest theta band, higher values at FC6 and F8 locations under low ventilation condition indicated that low ventilation could lead to relatively more drowsiness in rest condition, which could also be related with the relatively more preference for air movement and more SBS. For EEG task alpha band, higher value at P8 location under low ventilation condition indicated that the low ventilation could lead to less attention/concentration for task completion, which could also be related with the computerized tasks performance.
- For the machine learning based EEG pattern recognition, full-set features rates were the best for both rest and task conditions, as the rates were all above 95%. The patterns of cumulative reduction of features were different for the LDA and SVM classifiers. The LDA classifier had low point, while the SVM classifier decreased monotonically. The classification rate of LDA

went below 90% at around 140-170 features, while the classification rate of SVM went below 90% at around 70 features.

The EEG frequency bands can be used as a more objective metric to support and explain traditional subjective questionnaire-based methods and task-based methods, and as a useful input to improve the human-building interaction. Furthermore, the machine learning based EEG pattern recognition method can be utilized to classify different mental states under various indoor air quality conditions in a more objective and holistic way for human-building interaction. As already discussed in Chapter 5, user-dependent classifiers were used, which can achieve relatively high accuracy as a result of bypassing inter-person differences. The potential future study is to build a more general user-independent classifier with a much larger population by adjusting main differences in gender, age, personality, etc.

Chapter 8 Conclusions and recommendations

8.1. Overview

This thesis is based on the long-term vision that the wellbeing and work productivity of building occupants should be incorporated into a more balanced building design and operation. To achieve this vision, the thesis focuses on improving the understanding and implementation of the two-way human-building interaction, i.e. the impact of indoor environment on occupants and occupants' feedback to the building. The methods developed are subjective indicators, task-based indicators, and physiological indicators in particular. The correlations among the three indicators are also explored. Furthermore, the thesis also evaluates some aspects of the impacts through the building lifecycle platform.

Specifically, a preliminary experimental study (Chapter 3) was conducted, and the main indoor environments studied were indoor thermal environment and indoor air quality. Then a case study was conducted (Chapter 4) to evaluate the impacts of indoor environment on occupants through the LCC perspective for educational buildings, and the data used were based on the experimental results from the preliminary study (Chapter 3). The thesis then focused on human-building interaction in indoor environments using EEG method, and two experiments were conducted separately to study the impacts of indoor thermal environment (Chapter 5) and indoor air quality (Chapter 7), and the results were correlated with subjective indicators and task-based indicators. Machine learning based EEG pattern recognition method (Chapter 6) was investigated in details by using the data from EEG thermal experiment (Chapter 5), and the machine learning method formed the main feedback mechanism.

8.2. Major findings

8.2.1. Comparison between MV and PDV ventilation systems in the field (Chapter 3)

This field experiment utilized subjective questionnaires and computerized task-based tests to compare students' thermal sensation, sick building syndromes (SBS), and short-term performance under mixing ventilation (MV) system and passive displacement ventilation (PDV) system.

It was found that MV could lead to significantly larger draft sensation than PDV due to high air velocity from the overhead diffusers, but the two different ventilation systems did not cause significant difference in whole body draft acceptability. On the other hand, PDV led to significantly higher draft and colder sensation in the lower body level because the diffusers were located at the ground level, while draft distribution was perceived relatively homogenous in vertical direction in the MV room.

Due to the initial un-designed fan deficiency in the MV room, it was also found that higher CO₂ concentration was the main factor causing SBS related to head while both higher CO₂ concentration and lower RH contributed to SBS related to eye. Furthermore, SBS resulted from high CO₂ concentration and low RH could lead to decrease in short-term performance.

8.2.2. Impacts of indoor environmental quality on students' wellbeing and performance through life cycle costing perspective (Chapter 4)

The impacts of indoor environment on occupants through the LCC perspective for educational building were also investigated. A case study was conducted based on the experimental results from the preliminary study (Chapter 3). Specifically, the monetized metrics were the benefit of avoided sick leave days for the wellbeing and the benefit of weighted average marks for the performance. These metrics were

compared with other monetized values of building facilities and operational energy through the building life cycle.

For the baseline balanced weighting scheme a, the extra operational energy expenses are much more than the extra capital expenses. The PDV scenario has more benefit of avoided sick leave, while the MV IAQ 2 scenario has more benefit of increased average mark. The MV IAQ 2 scenario also has more total net benefit. For the benefits to extra expenses ratios, the MV IAQ 2 scenario has a larger ratio than PDV scenario (15.7 as compared to 6.1), which is mainly due to the lower extra expenses in MV IAQ 2 scenario.

For the sensitivity analysis of the life cycle costing for the balanced weighting scheme, the metrics are generally robust, as there are no abrupt changes when the individual metric varies within the range considered. The total net benefits are also significant, and the variations of total net benefits among different metrics are also comparable. The metric that caused the largest deviation of the benefits to extra expenses ratio is the energy tariff growth rate: 8.0 to 26.2 for MV IAQ 2 scenario, and 3.2 to 9.7 for PDV scenario. Other metrics have smaller deviation of the benefits to extra expenses ratios.

8.2.3. EEG methods for human-building interaction in indoor environment (Chapter 5 and 7)

Two chamber experiments were conducted. The first experiment investigated the indoor temperature, and the second experiment investigated the indoor air quality. For both two experiments, impacts of the indoor environment on subjective perception, work performance and EEG were studied. In particular, EEG asymmetrical activity was used as the physiological indicator for the indoor temperature environment, and the EEG frequency band was used as the

physiological indicator for the indoor air quality environment. For both the two experiments, the correlations between EEG and subjective questionnaire-based results, and between EEG and objective task results were explored. Furthermore, machine learning based EEG methods were also demonstrated.

In the indoor temperature experiment, the neutral condition was the most acceptable. For the general environment perception, mood and self-perceived performance, cool condition and neutral condition were similar, while warm condition was relatively less satisfactory. For the task performance, neutral condition led to the best performance than the other two thermal conditions. For the EEG frontal asymmetrical activity, trends of rest condition and task condition were similar: neutral thermal condition led to more positive/approach emotion than the other two thermal conditions, while the other two thermal conditions were similar. The EEG rest frontal asymmetrical activity was more related to the thermal acceptability metric, and the EEG task frontal asymmetrical activity also related well to the task performance. LDA machine learning classifier was also demonstrated, which could well classify the different mental states under three thermal conditions for both rest and task conditions in two feature ranges.

In the indoor air quality experiment, low ventilation led to more preference for air movement. For the breath sensation and eye sensation, the low ventilation condition also led to relatively worse perception. For the task performance, the overall trend also indicated that the low ventilation rate could lead to relatively worse task performance. For EEG rest theta band, higher values at FC6 and F8 locations under low ventilation condition indicated that low ventilation could lead to relatively more drowsiness in rest condition, which could also be related with the relatively more preference for air movement and more SBS as suggested by questionnaire. For EEG task alpha band, higher value at P8 location under low ventilation condition

indicated that the low ventilation could lead to less attention/concentration for task completion, which could also be related with the performance of computerized tasks. LDA and SVM machine learning classifiers were also demonstrated, which could well classify the different mental states under two indoor air quality conditions for both rest and task conditions.

8.2.4. Machine learning based EEG pattern recognition methods for human-building interaction under various indoor temperatures (Chapter 6)

Machine learning based EEG pattern recognition was further studied in details, and this method also forms the main feedback mechanism. The data used to explore the methods were from the indoor temperature experiment (Chapter 5). Specifically, the performance of various machine learning methods were compared, which further demonstrated the suitability of machine learning methods in the context of indoor thermal environment. Moreover, linear continuous features of mental states under various temperatures were found and checked by interpolation, which can be a potential way to establish more classes without conducting more experiments.

The performances of different classifiers were first checked for the full-set features. The LDA classifier had better performance (approaching 100%) than the NB classifier (93% for rest and 97% for task). The KNN classifier (91% for rest and 93% for task) performed slightly worse than the NB classifier. In general the machine learning methods were suitable in the indoor thermal environment context. The patterns of cumulative reduction of features were also checked. The LDA classifier had low points, while the NB and KNN classifiers decreased monotonically. From the full-set features to the location of LDA classifier's low point, the LDA classifier had the highest classification rate, and the NB classifier was intermediate, and the KNN classifier was the worst. In this range, LDA classifier also had the smallest

standard deviations among human subjects, while the NB and KNN classifiers had similarly larger standard deviations.

The linear continuous features were selected by interpolation method. For both the rest and task conditions, linear continuous features can be found for all human subjects for each case with inter-person differences. Higher selection threshold led to less selected features but higher average performance of these features, i.e. higher average classification rates.

8.3. Significance of research

The core of this research established EEG based methods for a potentially better human-building interaction. Specifically, the impacts of indoor thermal and air quality on occupants' wellbeing and performance were more objectively and accurately quantified by EEG indices, namely asymmetrical activity and frequency bands. These indices also helped to explain and correlate with traditional subjective indicators and task-based indicators. On the other hand, the machine learning based EEG methods in human-computer interaction domain were also explored in this research. Together with EEG indices, the machine learning based EEG methods can be the main feedback mechanism of wellbeing and performance to the building. With more channels and more user-friendly EEG based physiological equipment like the one in this research, the EEG method could be a crucial medium for the more accurate and objective human-building interaction in the future.

Furthermore, the incorporation of the wellbeing and performance of occupants into the building life cycle platform was also extended to other building types in this research, namely the educational buildings. Both a better human-building interaction using EEG based methods and the perspective through life cycle

platform can contribute to the incorporation of occupants' wellbeing and performance into a more balanced building design and operation.

8.4. Recommendations for future works

More types of environment and methods can be further studied. For instance, more types of indoor environment such as combined thermal and IAQ environment, noise environment or lighting environment could be explored. Other types of tasks that reflect different mental activities could also be used, and could be further correlated with EEG methods. More EEG physiological indices and machine learning based algorithms could also be explored.

For the machine learning-based EEG methods, more general user-independent classifiers by considering main differences such as gender, age, personality, occupation could be adjusted with a much larger population. More environmental conditions could also be established (e.g. more temperature levels) for machine learning training, which could work even better together with interpolation or even extrapolation. Furthermore, the incorporation of EEG into active building control could also be explored through the interface of EEG and building ACMV systems.

For the building life cycle aspect, the impacts of IEQ on physiological indicator can also be used as inputs into the life cycle platform. Furthermore, physiological indicator as a feedback mechanism can also be evaluated through the life cycle platform, since feedback mechanism also requires energy and resources during the building operation. A more comprehensive LCC study of educational building type could be explored, and other building types could also be explored. Finally, broader metrics not limited to monetary values that are used in LCC studies could also be used as inputs into the whole building LCA platform or social LCA aspects.

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Appendix A Supplementary figures for machine learning-based EEG pattern recognition methods

EEG pattern recognition methods

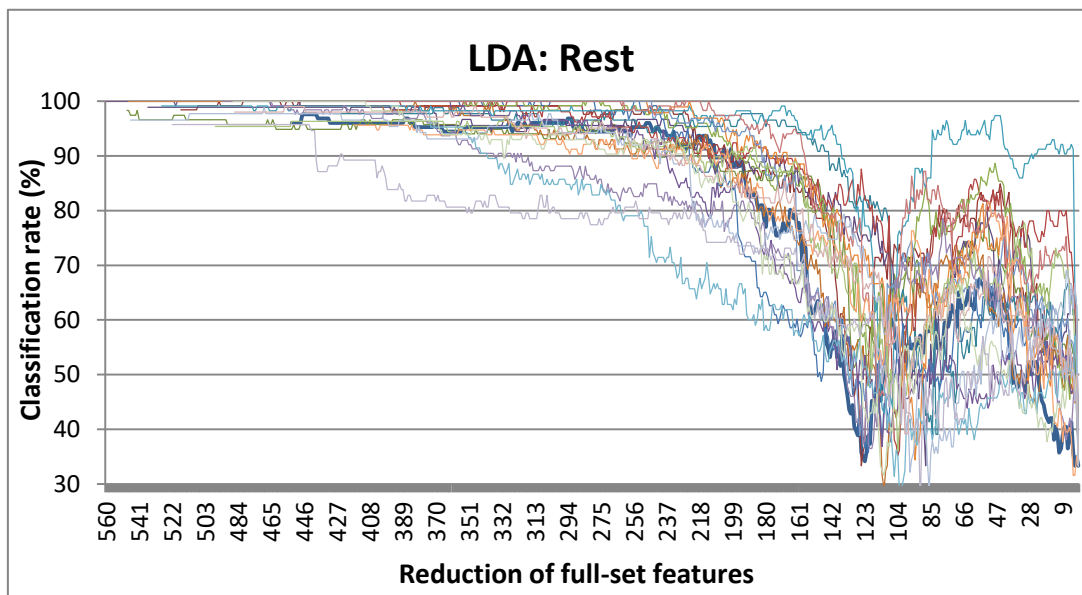


Figure A.8.1 Thermal experiment. LDA rest. Each line represents one human subject.

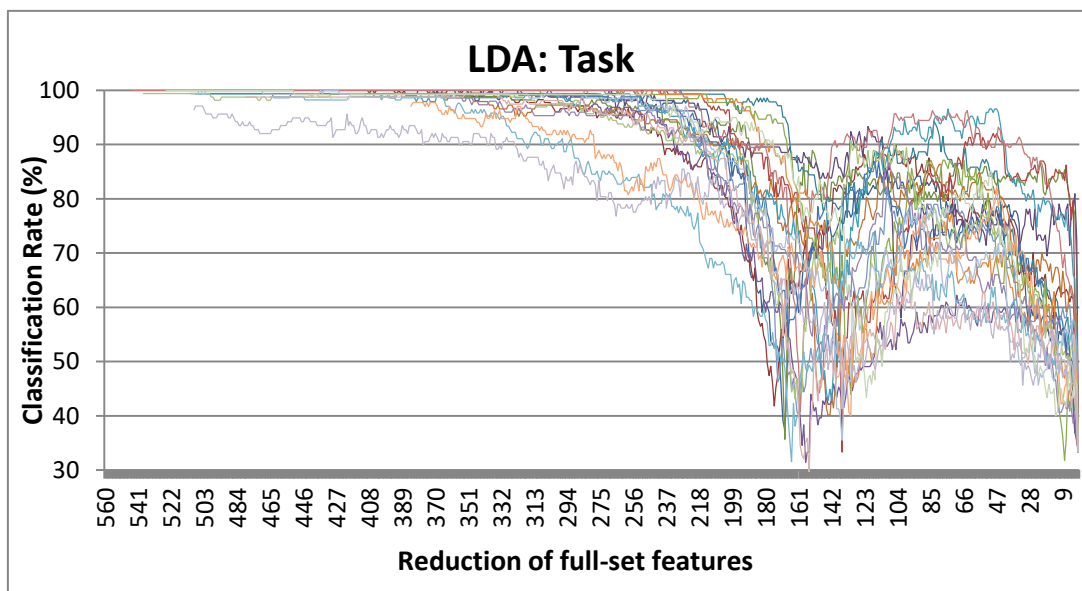


Figure A.8.2 Thermal experiment. LDA task. Each line represents one human subject.

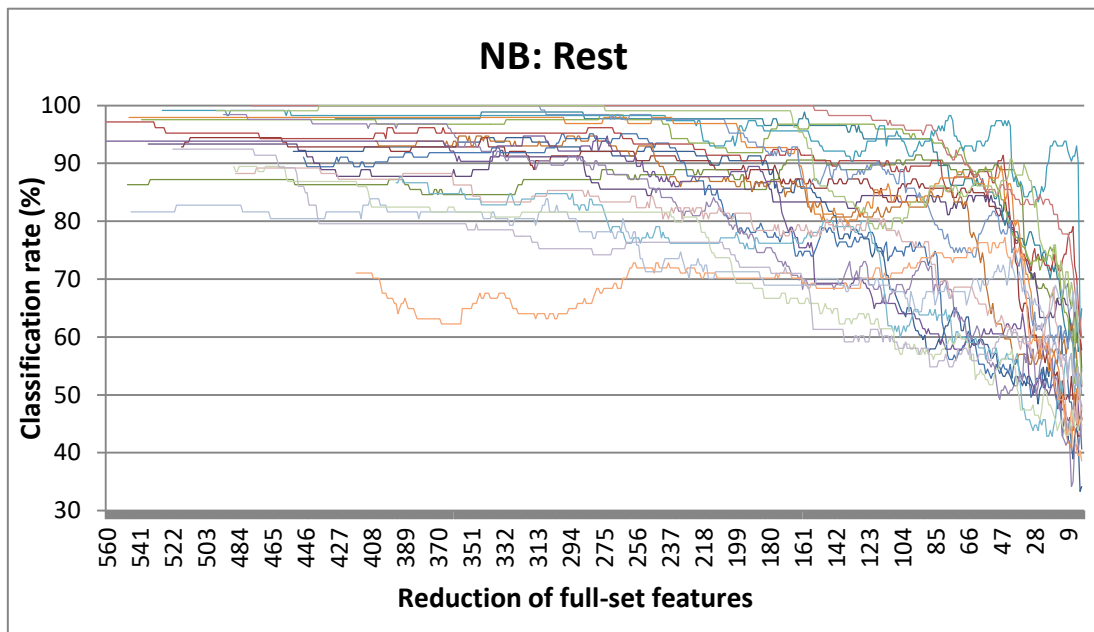


Figure A.8.3 Thermal experiment. NB rest. Each line represents one human subject.

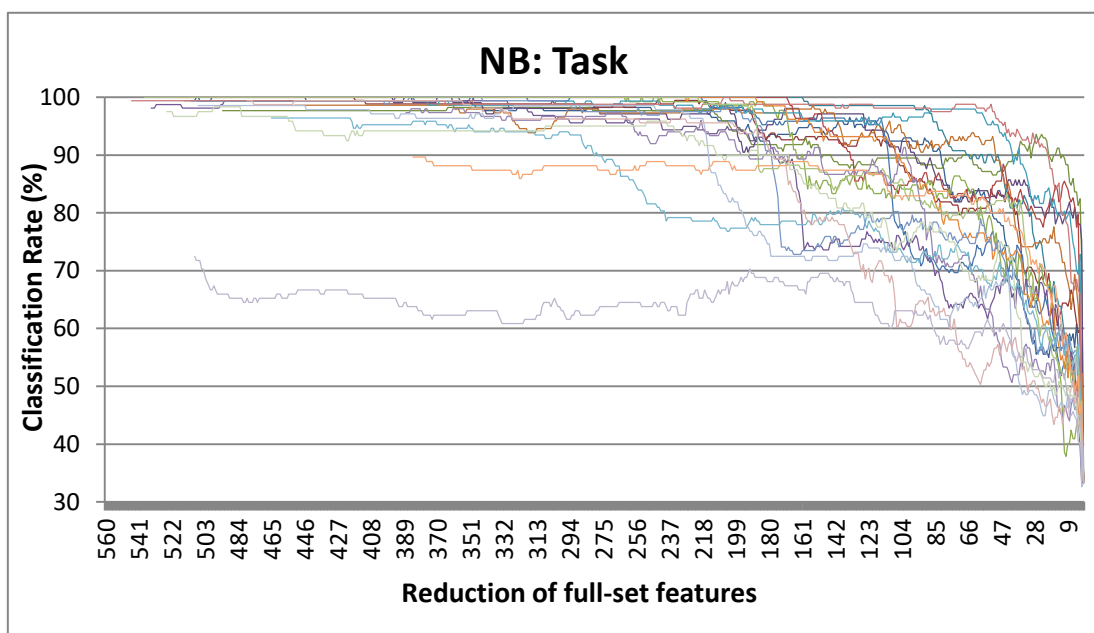


Figure A.8.4 Thermal experiment. NB task. Each line represents one human subject.

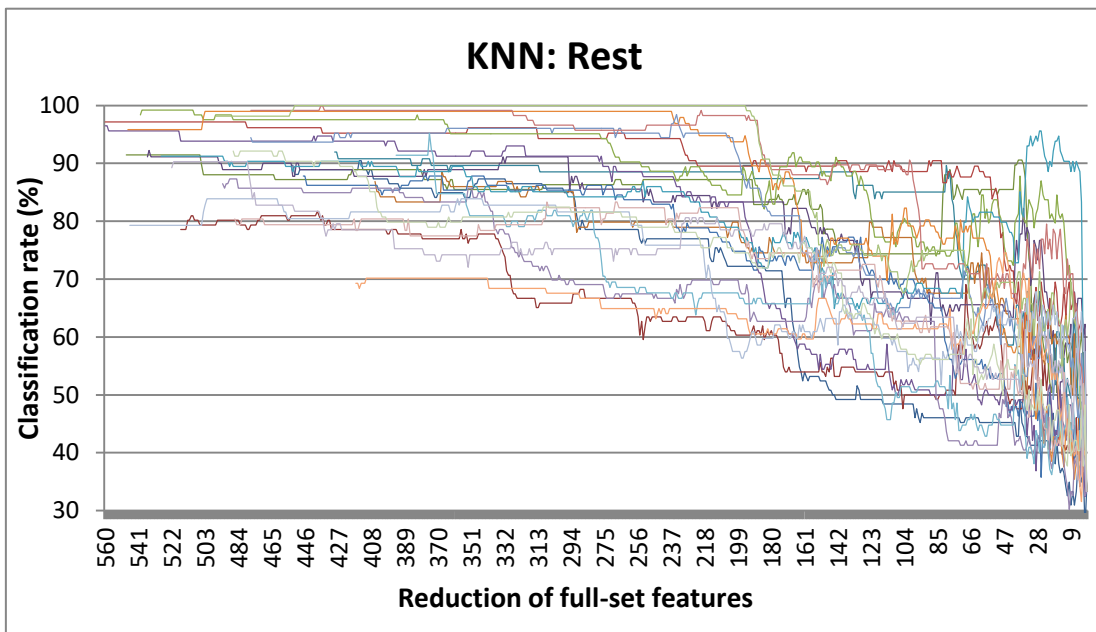


Figure A.8.5 Thermal experiment. KNN rest. Each line represents one human subject.

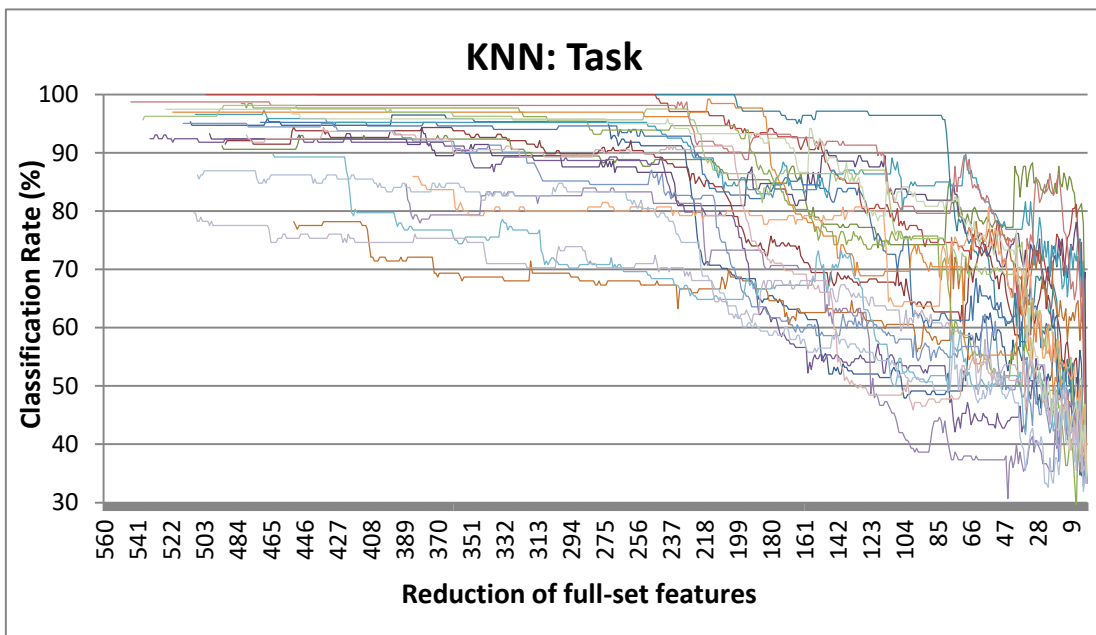


Figure A.8.6 Thermal experiment. KNN task. Each line represents one human subject.

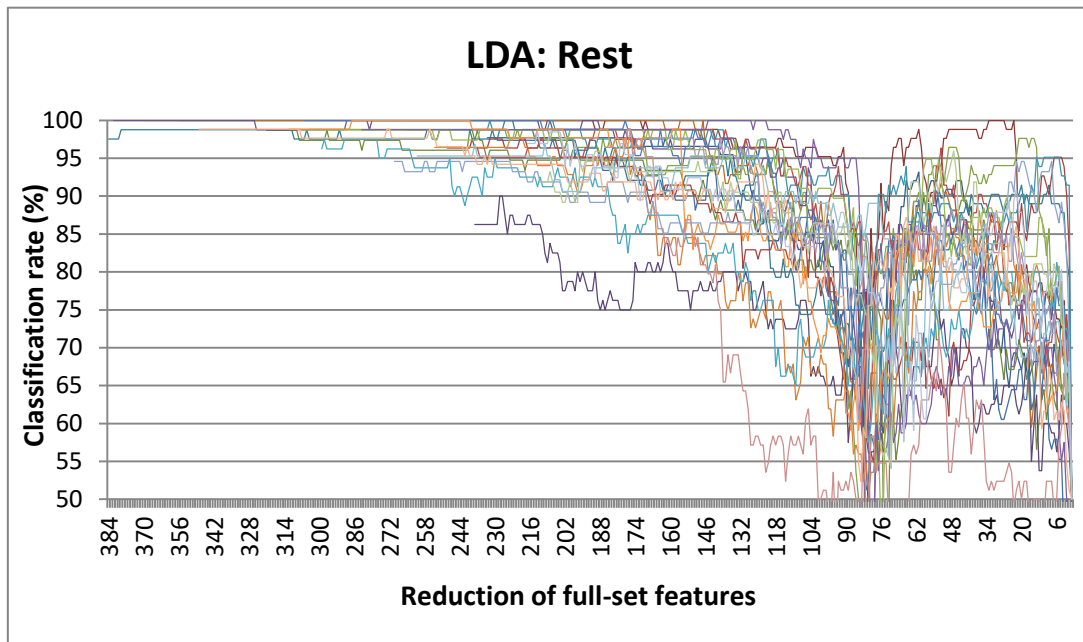


Figure A.8.7 IAQ experiment. LDA rest. Each line represents one human subject.

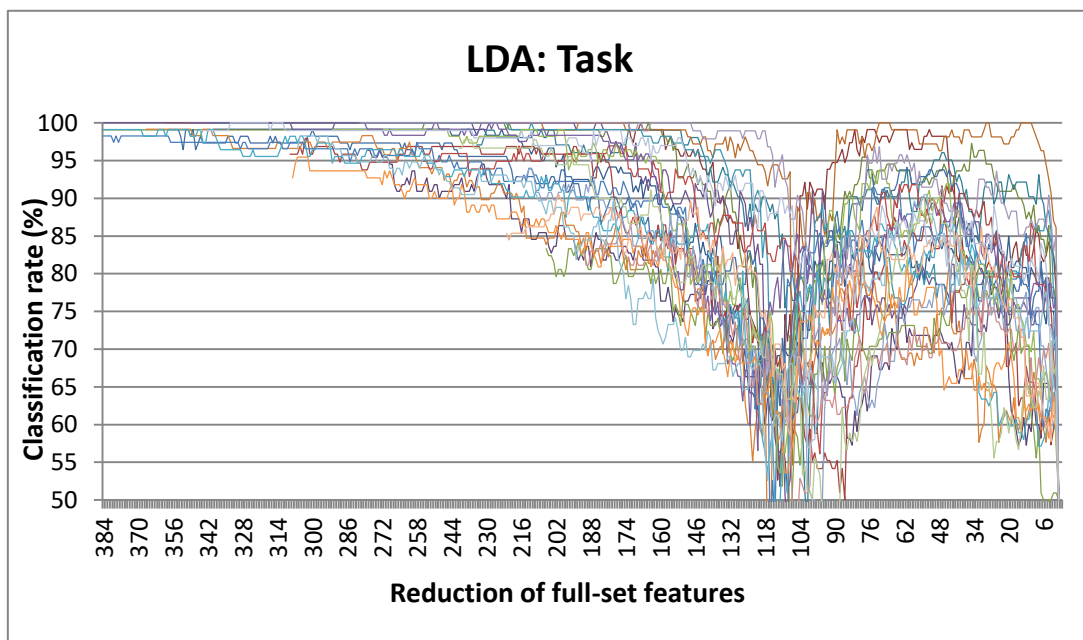


Figure A.8.8 IAQ experiment. LDA task. Each line represents one human subject.

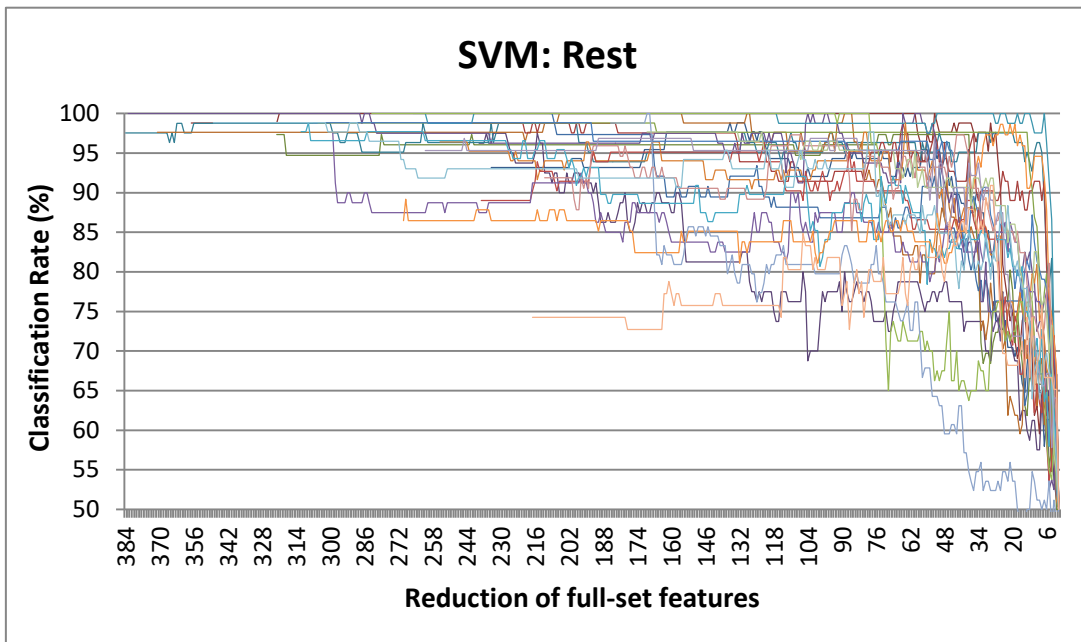


Figure A.8.9 IAQ experiment. SVM rest. Each line represents one human subject.

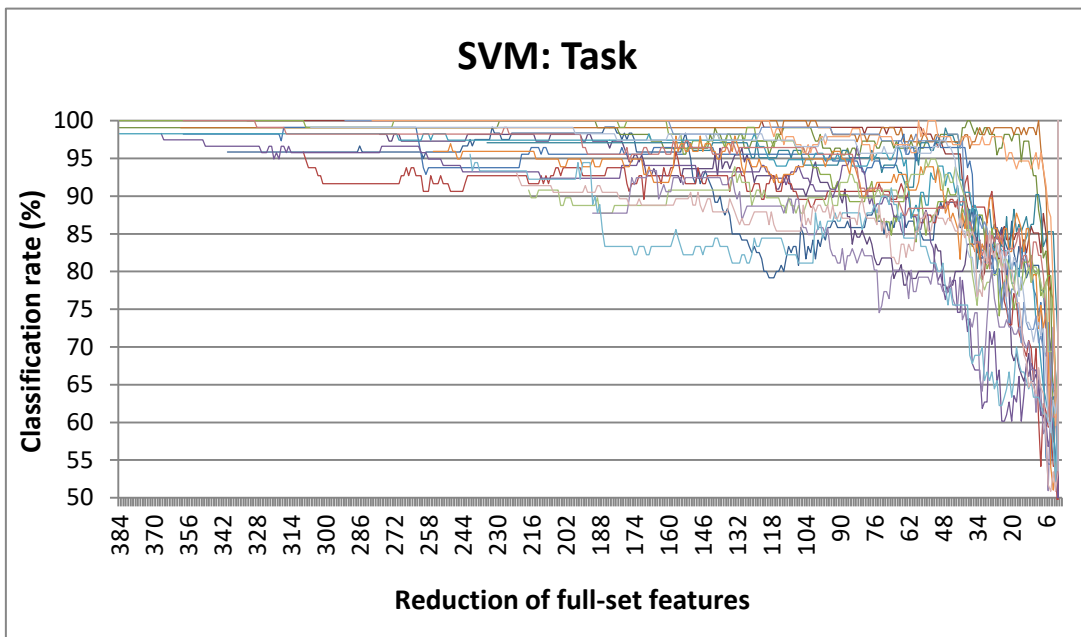


Figure A.8.10 IAQ experiment. SVM task. Each line represents one human subject.

Whole Body Thermal Comfort Acceptability

Very Unacceptable 1 2 3 4 5 6 7 Very Acceptable
(非常不可接受) (非常接受)

3. General Evaluation and Physiological Responses

3.1 General Indoor Environment

Prefer more draft (希望风大点)	1	2	3	4	5	6	7	Prefer less draft (希望风小点)
Too humid (湿度大)	1	2	3	4	5	6	7	Too dry (湿度小)
Large odor (异味大)	1	2	3	4	5	6	7	No odor (无异味)
Air stuffy (空气闷)	1	2	3	4	5	6	7	Air fresh (空气新鲜)
Noisy (不安静)	1	2	3	4	5	6	7	Quiet (安静)
Dark (灯光暗)	1	2	3	4	5	6	7	Bright (灯光亮)

3.2 Physiology Responses

Not Clear headed (头脑不清醒)	1	2	3	4	5	6	7	Clear headed (头脑清醒)
Headache (头痛)	1	2	3	4	5	6	7	No headache (头不痛)
Heavy-headed (头晕)	1	2	3	4	5	6	7	Not heavy-headed (头不晕)
Sleepy (想睡觉)	1	2	3	4	5	6	7	Not sleepy (不想睡觉)
Tired (疲劳)	1	2	3	4	5	6	7	Rested (轻松)
More runny nose (流鼻涕多)	1	2	3	4	5	6	7	No runny nose (不流鼻涕)
More Sneeze (打喷嚏多)	1	2	3	4	5	6	7	Not sneeze (不打喷嚏)
Nose blocked (鼻子堵塞)	1	2	3	4	5	6	7	Nose clear (鼻子不堵塞)
Nose dry (鼻干)	1	2	3	4	5	6	7	Nose humid (鼻不干)
Nose itching (鼻痒)	1	2	3	4	5	6	7	Nose not itching (鼻不痒)
More cough (咳嗽多)	1	2	3	4	5	6	7	No cough (不咳嗽)
Dry throat (咽干)	1	2	3	4	5	6	7	No dry throat (咽不干)
Irritated throat (咽喉痛)	1	2	3	4	5	6	7	No irritated throat (咽喉不痛)
Dry eyes (眼干)	1	2	3	4	5	6	7	Eyes not dry (眼不干)
Eyes smarting (眼痛)	1	2	3	4	5	6	7	Eyes not smarting (眼不痛)

Watering eyes (泪眼)	1	2	3	4	5	6	7	No watering eyes (没有泪眼)
Eyes itching (眼痒)	1	2	3	4	5	6	7	Eyes not itching (眼不痒)
Eyes strain (眼睛疲劳)	1	2	3	4	5	6	7	Eyes not strain (眼睛不疲劳)
Hands not flexible (手不灵活)	1	2	3	4	5	6	7	Hands flexible (手灵活)
More cold quiver (常打冷颤)	1	2	3	4	5	6	7	No cold quiver (不打冷颤)
Skin dry (皮肤干燥)	1	2	3	4	5	6	7	Skin not dry (皮肤不干燥)
Skin itching (皮肤痒)	1	2	3	4	5	6	7	Skin not itching (皮肤不痒)
Tinnitus (耳鸣)	1	2	3	4	5	6	7	No tinnitus (不耳鸣)
Affect hearing (影响听觉)	1	2	3	4	5	6	7	Not affect hearing (不影响听觉)
Irritating to the ear (刺耳)	1	2	3	4	5	6	7	Not irritating to the ear (不刺耳)
Stifle (窒息)	1	2	3	4	5	6	7	Not stifle (不窒息)
Chest tight (胸闷)	1	2	3	4	5	6	7	Chest not tight (胸不闷)
Anoxia (缺氧)	1	2	3	4	5	6	7	Not anoxia (不缺氧)
Breathing difficulty (呼吸困难)	1	2	3	4	5	6	7	No breathing difficulty (呼吸不困难)
Flu-like symptoms (有感冒症状)	1	2	3	4	5	6	7	No Flu-like symptoms (没有感冒症状)
Nausea (恶心)	1	2	3	4	5	6	7	No nausea (不恶心)

4. General Satisfaction of the environment

Generally dissatisfied with the environment (对环境总体不满意)	1	2	3	4	5	6	7	Generally satisfied with the environment (对环境总体满意)
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5. After completing computer-based tasks:

5.1 Mood

Nervous (紧张不安)	1	2	3	4	5	6	7	Relaxed (放松)
Unhappy (心情不愉快)	1	2	3	4	5	6	7	Happy (心情愉快)
Not energetic (没有精神)	1	2	3	4	5	6	7	Energetic (有精神)

Irritable (急躁)	1	2	3	4	5	6	7	Not irritable (不急躁)
Easily furious (易发怒)	1	2	3	4	5	6	7	Not easily furious (不易发怒)
Constrained (压抑)	1	2	3	4	5	6	7	Not constrained (不压抑)
Uneasy (心神不宁)	1	2	3	4	5	6	7	Not uneasy (心神安宁)
Gloomy (情绪低落)	1	2	3	4	5	6	7	Not gloomy (情绪不低落)

5.2 Self-perceived Productivity

Not full of vitality (无干劲)	1	2	3	4	5	6	7	Full of vitality (有干劲)
Low efficiency (效率低)	1	2	3	4	5	6	7	High efficiency (效率高)
Forgetful (健忘)	1	2	3	4	5	6	7	Good memory (记忆强)
Unable to Concentrate (注意力不集中)	1	2	3	4	5	6	7	Easy to Concentrate (注意力集中)
Not easy to decide (不易决断)	1	2	3	4	5	6	7	Easy to decide (决断)
No will to study/ work (不想学习或工作)	1	2	3	4	5	6	7	Willing to study/work (想学习或工作)
Not reactive (反应不灵活)	1	2	3	4	5	6	7	Reactive (反应灵活)
Difficult to think (思考困难)	1	2	3	4	5	6	7	Easy to think (思考不困难)
Thought unclear (思维不清晰)	1	2	3	4	5	6	7	Thought clear (思维清晰)

Please make sure that you have answered all questions. Thank you for your cooperation!

Appendix C Sample questions for computer-based tasks

Part I: Short-term Memory

1. Pair Recall: Please try to remember pairs of characters, and then recall the red character in each pair.

Group 1: Q-**A** W-**S** E-**D**
You have 15 seconds to remember these pairs.

Group 2: R-**F** T-**G** Y-**H**
You have 15 seconds to remember these pairs.

Please recall the red character in each pair:

Group 1: E- Q- W-
You have 15 seconds.

Please recall the red character in each pair:

Group 2: T- Y- R-
You have 15 seconds.

2. Sequence Recall: Please try to remember the words in sequence.

Group 1: material support expectation architect
You have 20 seconds to remember these words in sequence

Group 2: emotion turnover intention provide
You have 20 seconds to remember these words in sequence

Please write down the words in group 1 in sequence

You have 40 seconds.

Please write down the words in group 2 in sequence

You have 40 seconds.

Part II: Reaction Time

Reaction Time: Please key in the character
you see on the screen as quickly as possible.
You have 150 seconds to do this task

q



Part III: Perception

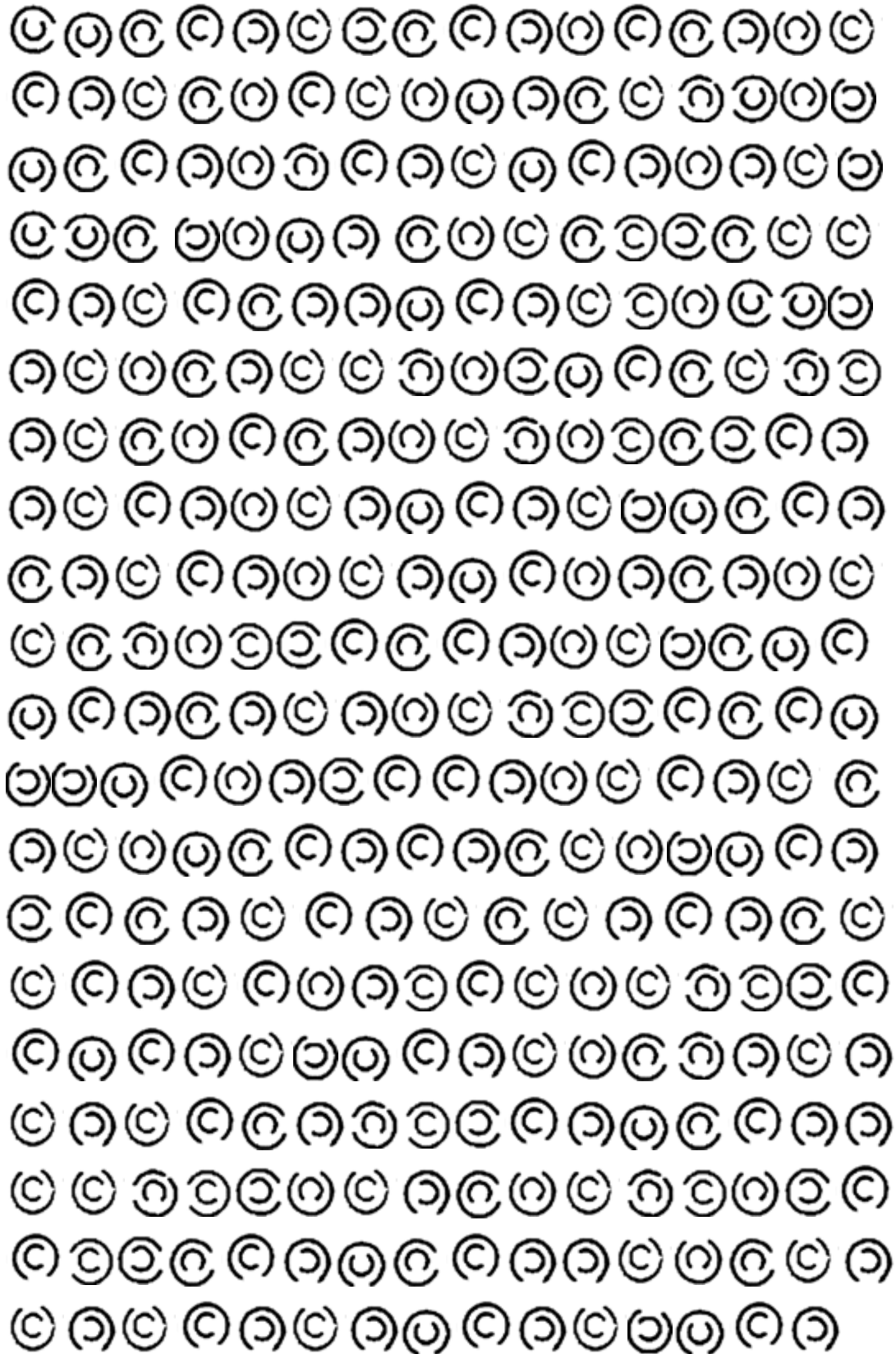
1. Visual Trace (5 minutes)

Please trace each curve and fill the ID into the boxes on the other side. Please ONLY use your eyes to trace. Assistance by fingers, mouse or pencil is forbidden (150 seconds).

1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
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12		
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15		
16		
17		
18		
19		
20		

2. Shape Identification

Please find all  and , and click them (300 seconds) .



3. Stroop Test

Stroop Test: Please judge whether the meaning of each word corresponds to its actual color as shown. If yes, please tick "√". If no, please tick "×". Please also choose the correct actual color as shown. (3 minutes)

	Red	Green	Blue
"√" or "×"	()	()	()
The actual color as shown	()	()	()

Part IV: Mental Arithmetic

Please give answer to each of the following:

$$\begin{array}{lll} 35 \times 35 = & 36 \times 34 = & 25 \times 52 = \\ 32 \times 45 = & 62 \times 49 = & 29 \times 56 = \end{array}$$