DEVELOPMENT OF NOVEL ASSESSMENT APPROACHES AND MODELS TO EVALUATE INDOOR ENVIRONMENTAL QUALITY (IEQ)

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Development of Novel Assessment Approaches and Models to Evaluate Indoor Environmental Quality (IEQ)

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Certificate of Originality

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Abstract

Indoor environmental quality (IEQ) has become one of the main concerns in built environment due to its effects on productivity, health and well-being. Poor IEQ can lead to discomfort and sickness, and businesses may need to suffer tremendous cost associated with the negative influences induced by substandard IEQ. Therefore, IEQ shall not be overlooked in building development and facility management practice.

IEQ can be categorized into a number of aspects, most popular ones include thermal comfort and indoor air quality (IAQ). Overall IEQ itself is also another perspective to evaluate building performance. The intra-relationship between factors of a particular aspect and the inter-relationship between aspects on overall IEQ have been found to be exceedingly complex, and these associations are usually task- and occupant-specific, which may change over time with lived experience by developing adaption and tolerance.

To tackle the intrinsic property of IEQ of being both subjectively and objectively influenced, this study proposes three assessment approaches to evaluate overall IEQ, thermal comfort and IAQ based on their respective natures. The inadequacy of current assessment methods and models is first identified. Literature search of thermal comfort field data and field study on sleeping thermal comfort are conducted to evaluate the performance of exiting thermal comfort models. Effects and implications of using inaccurate prediction models are also discussed.

Field surveys on physical environmental conditions and subjective IEQ responses are conducted in extreme living environments to determine the relationship between environmental quantities and occupant's acceptance, and to compare the new observations with established beliefs by acceptance prediction models. Discrepancies are found between predictions and actual data, suggesting the influence of contextual factors and adaptation on subjective responses to perceived environment.

In order to acknowledge and reflect the influence of occupant's response in prediction model, and allow flexibility of model parameters, an open probabilistic acceptance model using frequency distribution function is developed to handle diverse range of descriptive IEQ parameters. It makes model updating easier and is more robust in reflecting occupant's environmental perception compared to existing logistic regression model. It is recognized that the characteristics of data used for model development strongly affect the accuracy, therefore the relationship expressed by prediction model shall be updated with newly observed field data.

Subsequently, Bayesian updating protocol for thermal comfort and overall IEQ model is developed to propose a framework for updating the above-mentioned relationship. It is demonstrated with practical examples of existing thermal comfort model and IEQ regression model. Bayesian approach allows systematic updates of current beliefs (i.e. acceptance prediction models) with openly available field data and new observations. With the selection of target sample size and acceptable error based on managerial decision, this approach incorporates field settings into any existing model by considering the statistical significance of field data, even with a small sample size. It shall provide an achievable solution to the present challenges in establishing a reliable environmental acceptance prediction model.

Additionally, being the one with severe health consequences, IAQ assessment can be conducted objectively based on health standard, rather than solely relying on subjective sense. To minimize the demand for conducting full IAQ assessment which is resource intensive, this study proposes a step-wise IAQ screening protocol with various combinations of surrogate IAQ parameters. It successfully screens out premises with high risk of problematic IAQ and those with low probability. Further to this, a large-scale IoT-based IAQ screening using low-cost sensors grid is conducted to demonstrate the identification of environmental attributes that contributed to poor IAQ and to evaluate the performance of IAQ index.

The proposed novel assessment methods evaluate and predict IEQ from different perspectives – subjective-objective approach and objective-criteria approach, which shall facilitate indoor environmental management by providing an inclusive way to assess building performance.

Publications related to the thesis

Tsang, T. W., K. W. Mui, L. T. Wong and W. Yu (2020). "Bayesian updates for indoor environmental quality (IEQ) acceptance model for residential buildings." Intelligent Buildings International: 1-16.

Tsang, T. W., K. W. Mui and L. T. Wong (2020). "Investigation of thermal comfort in sleeping environment and its association with sleep quality." Building and Environment **187**: 107406.

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List of abbreviations

ACH	Air change rate
APD	Actual percentage dissatisfied
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEAM	Building Environmental Assessment Method
BRI	Building Related Illness
CBE	Center for the Built Environment
EAP	Express Assessment Protocol
EPD	Environmental Protection Department
FP/ FN	False positive/negative
GSHP	Ground-source heat pump system
HEPA	High-efficiency particulate air
HVAC	Heating, ventilation, and air conditioning
IAQ	Indoor air quality
IEQ	Indoor environmental quality
IoT	Internet of Things
ISO	International Organization for Standardization
LEED	Leadership in Energy and Environmental Design
MVAC	Mechanical ventilation and air-conditioning system
NREM	Non-rapid eye movement sleep
PD	Percentage dissatisfied
PMV	Predicted mean vote
$PMV_{2\text{-part}}$	Predicted mean vote by Lan et al's model
PMV_e	PMV adjusted for expectation
PMV_{new}	PMV adjusted with bias
PMV_{sleep}	Predicted mean vote by Lin and Deng's model
POE	Post-occupant evaluation
PPD	Predicted percentage dissatisfied
PSQI	Pittsburgh Sleep Quality Index
REM	Rapid eye movement sleep

SBS	Sick Building Syndrome
SD	Standard deviations
SDUs	Subdivided units
SWS	Slow wave sleep
TN/ TP	True negative/ positive
TSV	Thermal sensation vote
VPEs	Verbal probability expressions
WHO	World Health Organization

List of chemicals

ABC	Airborne bacteria count
C_6H_6	Benzene
C_7H_8	Toluene
C_8H_{10}	Ethylbenzene
C_8H_8	Styrene
CH_2Cl_2	Dichloromethane
CO	Carbon monoxide
CO_2	Carbon dioxide
HCHO	Formaldehyde
NH_3	Ammonia
NO_2	Nitrogen dioxide
NO_x	Nitrogen oxides
O_3	Ozone
Pb	Lead
PCP	Pentachlorophenol
PM	Particulate matter
PM_{10}	Respirable suspended particulate with a diameter of 10μm or less
$PM_{2.5}$	Fine suspended particulate with a diameter of 2.5μm or less
Rn	Radon
SO_2	Sulphur dioxide
TVOC	Total volatile organic compounds
VOCs	Volatile organic compounds

List of symbols

φ	Occurrence of conditions
μ	Mean
σ	Standard deviation
ε	Error
A	Percentage coverage of body surface area by bedding and bed (%)
A_D	Body surface area (m^2)
c	Thermal conductivity of bed (W/m^2K)
C	Coefficient for regression equations
C_h	Specific heat (kJ/kg°C)
c_r	Ratio of ε to difference between prior and measured acceptance
D	Permeance coefficient of the skin (g/sm^2Pa)
f	Area factor
h	Heat transfer coefficient ($W/m^2 \cdot K$)
I	Insulation (m^2K/W)
j	Environmental cases
k	Number of cluster in *k*-mean clustering
K	Constant, 6.45 (clo W/m^2°C)
L	Thermal load (W)
L_r	Likelihood ratio
M	Metabolic rate (W/m^2)
n	Sample size
O_d	Odd ratio
p	Pressure (Pa)
P	Probability
P_f	Specificity of test
P_s	Sensitivity of test
Q	Heat flow (W)
R	Thermal resistance (m^2°C/W)
RH	Relative humidity (%)
r_{pb}	Point-biserial correlation coefficient

T	Temperature (°C)
t	Thickness of bed (m)
v	Velocity (m/s)
W	Work (W/m^2)
w	Skin wittedness
$\tilde{x}$	Probability density function of normalized occupant votes for the environmental acceptance δ
x_i	Level of surrogate parameter in IEQ
y	Cumulative frequency distributions for the mass density functions of $\tilde{x}$
α	Sensitivity coefficient
δ	Acceptance with respect to environmental aspect
ε	Emissivity of the globe
θ_q	IAQ index
λ	Heat of vaporization of water (kJ/kg)
ρ_j	Acceptance with respect to environmental condition
ϕ_γ	Pollutant level
ϕ_γ^*	Fractional dose
$\phi_{\gamma,0}$	Exposure limit
ς	Ratio of body area not in contact with the bed

Subscripts

'	Post-treatment
$_0$	Prior
$_a$	Air
$_{avg}$	Average residential unit
$_b$	Bed
$_c$	Convection
$_{cl}$	Clothing
$_{cod}$	Conduction
$_d$	Unsatisfactory IAQ
$_{df}$	Diffusion
$_e$	Evaporative

ex	Expired air
g	Globe
i	Environmental aspect; i = 0: overall IEQ, i=1: thermal, i=2: IAQ, i=3: aural, i=4: visual
l	Heat loss
m	Measured
M	Maximum
n	Neutral
nb	Not in contact with bed
o	Operative
out	Outdoor
p	Predicted
q	Number of IAQ parameter
r	Radiation
rad	Radiant
res	Respiration
s	Satisfied
sk	Skin
sn	Sensible
t	Total
T1	IAQ index no action threshold
T2	IAQ index test-treatment threshold
u	Unsatisfied
w	Weighted

Chapter 1. Introduction

1.1. Background

Indoor environmental quality (IEQ) is a major concern in built environment as it affects productivity, health and well-being. It is a broadly defined building performance indicator that can be determined by many factors including but not limited to environmental conditions and occupant's acceptance. IEQ in commercial buildings has been extensively studied due to the detrimental loss in productivity from substandard indoor environment (Nagata, Mori et al., 2018). Many design guides and building standards have been developed for office buildings to assess and evaluate the building performance against a set of comfort criteria. As workplaces are more uniform, and occupants have less control over the environmental settings, the extent of adaption behaviour is limited. Occupant's responses towards the perceived environment in office are therefore relatively consistent.

Less focus has been put onto evaluating IEQ at home despite people spend over 65% of their time in residence (Klepeis, Nelson et al., 2001). Indoor environment in a residential building is more dynamic and varying than that in an office (Ioannou and Itard, 2015). More interactions between occupants and dwellings can be expected at home since they have greater control over the surroundings. Adaptation behaviours, for example opening or closing window for ventilation and adjusting the level of insulation provided by clothing, may be taken to improve comfort. Occupant's perception and adaption to the environment may also greatly influence the satisfaction and comfort level towards IEQ (Mui, Tsang et al., 2019, Tsang, Mui et al., 2019). With population expansion and urbanization, more people are now living in high-rise multi-unit residential buildings in cities (Andargie, Touchie et al., 2019). Given this fast-changing housing situation of the world, our understandings on IEQ in residential environments shall be enhanced and updated.

In addition, urban development has prompted the emergence of large-scale multifunctional mall designed to provide high-quality and comfortable shopping experience for customers. Developers in Hong Kong have expressed their interests in adopting sustainable building development and operation strategies by actively engage in Building Environmental Assessment Method (BEAM) assessment and Leadership in Energy and Environmental Design (LEED). Some even seek ways to further improve the IEQ to provide an indoor environment above local standards through the use of smart technologies and user engagement (NWD, 2019).

With growing attentions on IEQ and its effects on health, comfort and productivity, comprehensive methods for assessing overall IEQ and the related environmental components are therefore necessary for building designers and engineers to evaluate occupant's satisfaction and comfort level at various places. Existing assessment methods evaluate an environment objectively, subjectively or from a combination of both perspectives. All having their own pros and cons with respect to resource requirement, ease of implementation, accuracy, representation and effectiveness. This thesis aims at identifying the major inadequacies of current IEQ assessment methods and developing novel assessment approaches to evaluate building performance and to improve IEQ satisfaction predictions, which shall facilitate indoor environmental management.

1.2. Existing approaches and assessment methods for evaluating IEQ

IEQ is an intricate issue. Environmental comfort can be interpreted as "the absence of unpleasant sensations which has a positive effect on well-being" (Feige, Wallbaum et al., 2013, p. 11). It can be highly subjective, still it is possible to identify factors that most people agree to be unappealing. Comfort can be categorized into three main aspects: i) physical comfort, which describes the comfort brings about by environmental parameters like air temperature (T_a), air quality and noise; ii) functional comfort, which refers to factors that affect work productivity, for example disturbances and distance from functional areas; and iii) psychological comfort, which concerns about the individual and interpersonal space-related factors like space, privacy and control over the environment (Feige, Wallbaum et al., 2013). This quantitative mechanical objective-criteria approach evaluates the building performance through collective assessment of individual factors within premises (Fleming, 2004). Overall comfort is therefore the combination of occupant's productivity, physical and psychological health.

Some take an alternative subjective behavioural approach as the indicator of building environmental performance. Rather than comparing the indoor environment with a number of technical performance metrics, this combined quantitative and qualitative approach views occupant's perception towards the environment as more relevant assessment criteria (Fleming, 2004). Behavioural environment includes distraction, interaction and informal interaction points, which alongside with physical environment, is found to have an impact to overall comfort and thus productivity (Haynes, 2007).

Subjective-objective approach therefore relates occupant's subjective responses with environmental quantities, using occupant's acceptance as evaluation metrics.

IEQ assessment can be done by investigating one or more factors that affect occupant's comfort and satisfaction towards the perceived environment. Single-domain studies evaluate the building performance based on a particular aspect of IEQ, with thermal comfort and indoor air quality (IAQ) as more popular areas of research (ISO, 2005, Andargie, Touchie et al., 2019, ASHRAE, 2019). Multi-factor studies on the other hand assess two or more IEQ factors concurrently, regardless the factors are discrete or continuous. The relative importance of factors is usually identified and the overall IEQ may be considered as a combination of weighed individual parameters (ISO, 2012, Andargie, Touchie et al., 2019).

There are objective and subjective ways to assess IEQ. Objective assessments utilize devices and instruments to capture a selected period of spatial and temporal physical state of IEQ in premises, while subjective assessments rely on surveys and interviews to understand occupant's comfort and satisfaction, which are the major interests of building operators (Heinzerling, Schiavon et al., 2013). Both methods have their own benefits and drawbacks, which are further discussed in Chapter 2 of this thesis.

Research on IEQ modelling aims at identifying the deterministic causal relationships between environmental quantities and occupant's comfort. To this end, these associations are assumed to be purely physical and can be expressed by mathematical equations (Baggs and Chemero, 2019, Willems, Saelens et al., 2020). Two basic types of models have been established: i) subjective-objective method, which relates subjective comfort collected by surveys and objective measurements, and gives single-variable, linear or multivariate regression equations that predict individual and overall IEQ satisfaction; and ii) objective-criteria, which comfort criteria, established by previous subjective-objective studies or by expert's opinion, are compared with objective measurements to determine the IEQ assessment class (Heinzerling, Schiavon et al., 2013). Both methods eventually combine sub-indices into overall IEQ index through weighting process and compare the overall index with a fixed set of range that defines IEQ level.

Many adopt the objective-criteria method to evaluate building IEQ, since the subjective nature of survey lack universal judgement (Asadi, Mahyuddin et al., 2017). For those use both subjective and objective methods to assess an indoor environment, some would further identify the association between subjective responses and objective measurements. One very common example is thermal comfort research that relates thermal sensation vote (TSV) (a subjective response) with operative temperature (T_o) (an objective parameter), and compares the relationship with the well-established PMV model (Fanger, 1970).

1.3. Discrepancies between predicted and actual comfort and satisfaction

A lot of IEQ-related subjective research has found that occupant’s actual responses towards the perceived environment are different from predictions by existing models. Discrepancies found in thermal comfort models and IEQ models can be attributed to contextual factors and perception, which are seldom considered in physical models due to their subjective nature. There have been attempts to address the inadequacy by collecting and incorporating adaption behaviour from field survey into prediction model. An adaptive thermal comfort model based on large sample size of thermal comfort field studies was therefore developed to take occupant’s behaviour adjustment, physiological and psychological adaption into account (de Dear and Brager, 1998), which has been implemented in ANSI/ASHRAE Standard 55-2010 Thermal Environmental Conditions for Human Occupancy (ASHRAE, 2010).

Notwithstanding the improvements made to existing models, studies suggest people still feel dissatisfied even if building comfort requirements are met (Burge, 2004). Although some comfort criteria are originally derived from subjective-objective studies, the relations may be outdated and do not necessarily fit for all premises. Biases may exist in the dataset used for model development. Other subjective comfort factors that can affect comfort and satisfaction may not be reflected in these criteria. The selection of statistical processes for analysing the data also significantly affects the prediction results (Majcen, Itard et al., 2013). Existing models may not consider the differences of various types of indoor environments, and as for the overall IEQ prediction, the effect of inter-category relationship between individual IEQ factors and overall IEQ has not been addressed in most IEQ models. The assessment classes of comfort criteria also lack justification and are not always aligned with occupant's actual sensations (Heinzerling, Schiavon et al., 2013).

From the above, it can be seen that IEQ has been defined with a broad spectrum of comfort features, including physical environment, psychological health, interaction and disturbance, etc., each having different degrees of objectivity. Thermal comfort, for example, is objectively modelled by identifying the relationship between physical heat balance mechanism and thermal sensation, and thus the acceptance. It is however that the effect of thermal load on thermal sensation and acceptance can be largely depended on subjective factors include perception, adaption and tolerance. Therefore, a pure objective-criteria approach for assessing thermal comfort cannot truly reflect occupant's comfort sense. Subjective-objective assessment with updated relationship can then minimize the discrepancies between prediction models and actual responses. Some aspects, for instance IAQ, can be evaluated subjectively by sense when pollutant levels are below health hazard level. Sense becomes rather unreliable when pollutant levels approach hazardous limits, as a result objective-criteria approach is required to identify problematic IAQ. It is therefore essential to evaluate IEQ using different approaches based on the nature and characteristics of the assessment.

1.4. Objectives

As IEQ significantly affects our health and comfort, IEQ assessment is essential in determining whether the environment can provide a good staying experience. Despite all the research efforts on identifying the discrepancies between predicted and actual comfort and satisfaction, existing buildings are still designed and operated according to comfort criteria such as comfort zone, building standards and guidelines, without factoring in the actual occupant's response towards the perceived environment.

To minimize the performance gap and improve current assessment methods for individual and overall IEQ satisfaction prediction, incorporation of the missing elements in existing methods for a more comprehensive, realistic and efficient IEQ assessment is of utmost importance. An accurate and updated subjective-objective comfort model that incorporates the significance of field data may help to improve comfort and satisfaction prediction, and therefore assessing an indoor environment based on the distinctive thoughts and perceptions of the building occupants (Fleming, 2004). While it is no doubt that a mathematical model with more factors and is derived from a large database gives more precise predictions, more resources will be required for conducting the assessment, which may not be cost-effective from an engineering point of view.

This study aims at proposing three novel IEQ assessment approaches for evaluating individual and overall IEQ. Proposed frameworks are designed to minimize the resources required for assessment while balancing the assessment and model prediction accuracy. Subjective-objective prediction models are developed to improve prediction accuracy by ameliorating the relationship between environmental quantities and occupant's satisfactions. The open acceptance model for IEQ and Bayesian updating framework for existing thermal comfort and IEQ models provide the flexibility in incorporating more model parameters and allow model updating with newly observed field data.

In addition to improving the subjective-objective modelling approach, an objective-criteria screening approach is proposed to reduce the number of parameters to be measured and derive risk of problematic IAQ with engineering accuracy. An Internet of Things (IoT)-based sensing network is applied to identify the environmental attributes that contribute to IAQ problems for long-term IAQ monitoring.

The objectives of this study are:

1. To review and identify the obstacles and difficulties in current IAQ, thermal comfort and IEQ assessment and satisfaction modelling;
2. To identify the discrepancies between thermal comfort field responses and predictions by existing models, and to recognize the consequences of using inaccurate prediction models for research and practical purposes;
3. To evaluate the performance of IEQ comfort model in extreme environment and to develop a novel IEQ satisfaction prediction model with flexibility in number and type of parameters based on occupant's psychological perception;
4. To develop mathematical approaches for thermal comfort and IEQ model updating based on newly observed field information; and
5. To develop IAQ screening assessment protocol and implement IoT-based low-cost sensing network for monitoring and facilitating cost-effective IAQ management.

1.5. Research scope

In regard to the objectives listed in the above paragraph, this study is divided into the following five tasks:

Task 1: Understanding the difficulties of IEQ assessment and modelling

Literature review is conducted to understand the essence of IEQ, IEQ assessment methods and models and to identify the impediment and complication in the process. IAQ and thermal comfort, which are the major environmental factors that influence overall IEQ satisfaction, are first discussed, and later the overall IEQ as a whole is considered. This task aims at recognizing current obstacles and aversion in assessing IEQ, thus paves the way for the development of simpler, appropriate and cost-effective assessment approaches for evaluating IAQ, thermal comfort and overall IEQ with minimum investment of material and manpower resources.

Task 2: Identification of discrepancies between thermal comfort field responses and model predictions

Step 2.1 Identification of performance gap in prediction model and its effects and implications

To recognize the performance gap between field data and predictions by models, and the consequential problems of misusing these inaccurate models, a thorough literature search is conducted to gather field thermal responses. Example application of prediction model is presented, and the resulting disparities estimated by field responses and prediction model are determined. This task identifies and demonstrates the negative consequences of using an inaccurate and outdated prediction model in research and practical application.

Step 2.2 Investigation of sleeping thermal comfort responses in dorm

Dormitory thermal environment during sleep is also studied. Thermal sensation responses are compared to model predictions, and association between sensation and sleep quality is determined. Results demonstrate that consistent and unified building thermal environment and thermal comfort model may not be suitable for all settings. Occupant's perceptions and preferences observed in different indoor space play crucial roles in determining the level of satisfaction to an environment, which shall be reflected in existing satisfaction prediction models.

<u>Task 3: Evaluation and development of IEQ comfort model</u>

Step 3.1 Investigation of IEQ responses in extreme living environments

To identify the discrepancies between actual field responses and predictions by existing models, surveys are conducted to investigate the IEQ responses from occupants living in very small residential units. Thermal comfort, IAQ, visual and aural environments are evaluated objectively by physical measurements and subjectively through interviews. Results from this task help us understand the effect of perception, adaption and tolerance on subjective IEQ responses in extreme environment, which provide insights into improving existing IEQ assessment models by incorporating subjective responses collected in field.

Step 3.2 Development of open acceptance model for IEQ

To acknowledge and reflect the influence of contextual factors on IEQ acceptability, an open probabilistic acceptance model that uses frequency distribution functions of occupant's responses towards four major IEQ parameters (i.e. thermal comfort, IAQ, aural and visual comfort) is proposed and developed. While extreme environment is rarely seen in buildings, zero acceptance beyond measurement range in cumulative frequency distribution can be inferred as environmental acceptance from occupants rather than just the building designers or operators. This model is flexible in a diverse range of descriptive IEQ parameters as well as feasible to be adopted using openly available IEQ acceptance data. Simple modelling method also allows easy model updating by adding newly observed data incrementally. The task presents a new approach to weigh in occupant's perception and subjective responses into prediction model.

Task 4: Development of Bayesian updating framework for model updating

In this task, Bayesian updating framework is introduced for thermal comfort and IEQ model updating. Based on existing prior information (i.e. existing model) and newly observed data, the posterior can be estimated with respected to a selected acceptable error and a target sample size. This updating framework allows the incorporation of field settings and occupant's perception into existing models even with a small sample size. Bayesian updating shall be able to improve model accuracy and give more realistic predictions that reflect occupant's subjective responses.

Task 5: Development of objective-criteria approach for IAQ assessment

Step 5.1 Development and implementation of step-wise IAQ screening strategies

Current objective-criteria IAQ assessment methods are resource-intensive. People may lack incentive to monitor and maintain good IAQ, thus exposing themselves and others to potential health risks. This task develops a step-wise screening approach with the use of dominant and representative IAQ parameters to assess an indoor environment. IAQ indices with one, two and three parameters are proposed to identify poor IAQ with respect to a range of engineering acceptable accuracies. A decision-making framework for IAQ monitoring and mitigation is also proposed to facilitate better and more cost-effective IAQ management.

Step 5.2 Implementation of IoT-based low-cost sensing module for IAQ monitoring

To demonstrate the use of IAQ index in identifying problematic IAQ, a large-scale IoT-based sensor network is implemented in a shopping mall to collect long-term spatial and temporal IAQ information. Different IAQ indices are used to identify environmental attributes that contribute to poor IAQ. This task signifies the feasibility of using low-cost IAQ sensors to monitor and screen potential risks of problematic IAQ for precautionary remediation measures.

1.6. Organization of thesis

The introductory chapter has set forth the background and research interests of this study. The aim is to recognize the performance gap of existing prediction models and to develop simple yet effective IEQ assessment approaches for evaluating individual and overall IEQ. The objectives and research scope have been identified and described in the above sub-sections. The structures and findings of this study are introduced in the following chapters. A flowchart of the organization of this thesis is summarized in Figure 1.1. Figure 1.2 shows an overview of how this thesis tackles on each of their unique natures by introducing new assessment methods through different approaches.

Reviews on current IEQ assessment methods and models are exhibited in Chapter 2. The complexity of IEQ influencing factors are studied and categorized. Methods for assessing IAQ, thermal comfort and overall IEQ, and occupant's responses prediction models are reviewed and discussed. Research gaps in the field are defined and the research needs for developing suitable and cost-effective assessment approaches for evaluating individual and overall IEQ with justifiable resources investment are proposed.

With the aim to identify the performance gap of thermal comfort assessment models, Chapter 3 investigates the discrepancies between field data available in literature and predictions by the Fanger's PMV/PPD model to discuss the consequences of relying on an inaccurate model. Application of PMV model for estimating energy saving potential is presented, and the resulting energy consumptions estimated by field responses and PMV model are determined. The deviation of the results indicates the potential problems of using inaccurate prediction models for research and practical uses. Further to evaluating thermal comfort model for awakening state, sleeping thermal comfort in dormitory is examined. The performances of existing sleeping thermal comfort models are assessed and the associations between sleeping thermal environment and thermal satisfaction are established. The importance of identifying different thermal comfort requirements and prediction models for different daily activities is discussed.

In Chapter 4, IEQ responses from occupants living in very small residential units in Hong Kong is investigated. Field measurements and interviews with occupants are conducted to collect objective IEQ parameters and subjective IEQ responses in order to identify the subjective-objective relationship between occupant's responses and perceived indoor environment. The uniqueness of these environments and its impact on our understanding on IEQ in residential environments are discussed. IEQ data gathered from average residential buildings in Hong Kong are compared and a residential IEQ model developed previously is evaluated with the newly acquired data. Based on the field results obtained, an open probabilistic acceptance model for IEQ is proposed which can genuinely reflect occupant's responses to environmental conditions. This model uses frequency distribution functions of occupant's responses towards major IEQ factors, which allows flexibility in model updating with the addition of newly obtained data. Simple modelling process also enables a diverse range of descriptive IEQ parameters to be factored in. Its prediction performance is compared to existing IEQ logistic regression model.

To improve the prediction accuracy of existing model, Chapter 5 proposes a Bayesian updating protocol to systematically update current environmental comfort beliefs. With openly available IEQ data, Bayesian updating framework incorporates the statistical significance of field settings and occupant's perceptions into existing models. It is demonstrated using Fanger's PMV/PPD model and IEQ regression model. Updated model shall give predictions closer to results collected in the field, therefore reflecting occupant's subjective responses that are distinct from purely physiological responses to environment obtained in experiments. This allows updating of the subjective-objective relationship of current prediction models to improve model accuracy and applicability. The results shall provide an analytical solution to building operators regarding the choice of environmental parameters in building design and management.

With reference to an IAQ index methodology proposed formerly, Chapter 6 takes a step further to develops a step-wise IAQ screening protocol that uses representative IAQ parameters to assess an indoor environment. The sensitivity, specificity and effectiveness in identifying IAQ problems using one, two and three surrogate parameters are evaluated and discussed. A screening and decision-making framework for IAQ management is presented and the usefulness of each screening step is assessed. Further to this, the feasibility of using IoT-based IAQ sensing modules for problematic IAQ screening is investigated. Relations between IAQ indices and environmental attributes that contribute to poor IAQ are explored. High-risk factors are determined such that corresponding precautionary measures can be done to prevent the occurrence of IAQ problems.

At last, Chapter 7 summarizes the key developments of this thesis. The significances and contributions of research efforts presented in different chapters are highlighted and discussed. Future research opportunities are also explored.

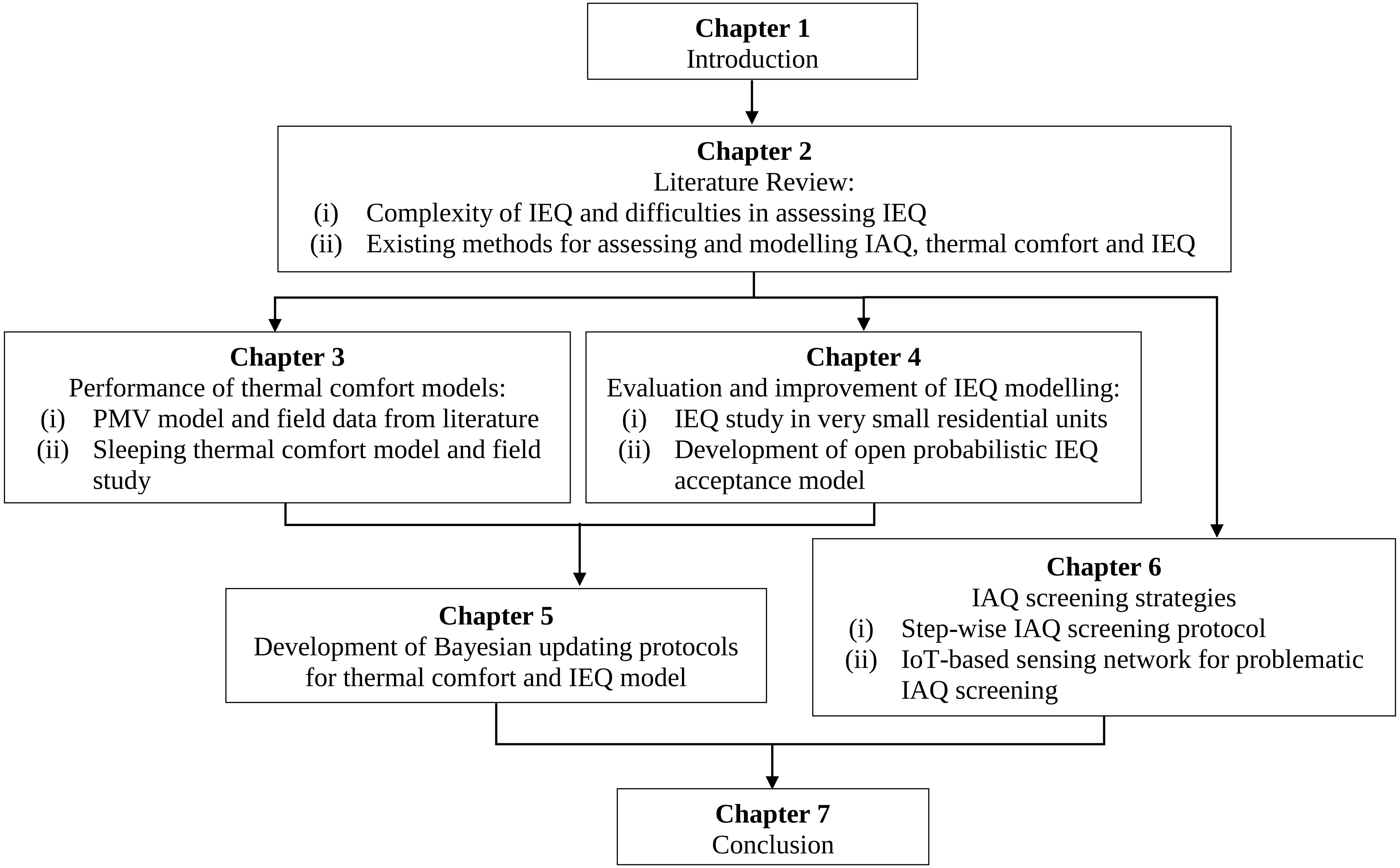


Figure 1.1 Organization of thesis

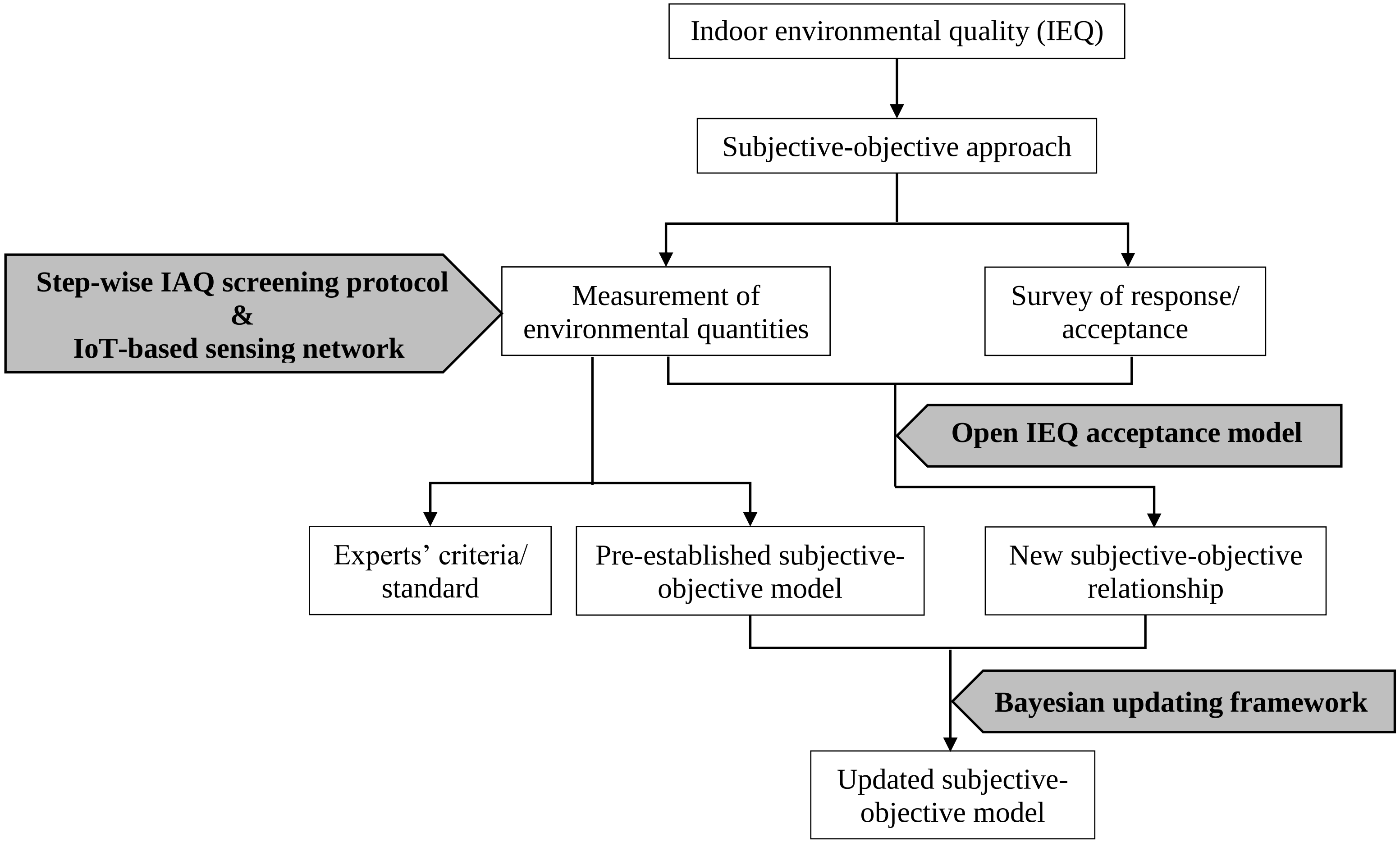


Figure 1.2 Overview of methodology

Chapter 2. Literature Review

2.1. Introduction

Indoor environmental quality (IEQ) relates to the environmental conditions that affect the acceptability of the indoor environment. With increasing concerns about building sustainability, compatibility between aesthetic, green and IEQ are sought to safeguard a healthy, comfortable and productive indoor environment (ASHRAE, 2016). The below paragraphs in this sub-chapter put together a brief introduction on the importance of assessing IEQ and the effects and impacts of substandard IEQ on building occupants. The remaining parts of this chapter are organized into two sections to review i) IEQ influencing factors in indoor environment; and ii) methods for assessing and modelling IAQ, thermal comfort and IEQ. Lastly, a summary of the literature review and the research gaps identified are outlined. The research needs for developing simpler and cost-effective assessment approaches for evaluating thermal comfort, IAQ and overall IEQ with justifiable resources investment are propounded.

2.1.1. Health impacts

Research has linked a range of environmental factors with both short- and long- term impacts on building occupants. Common short-term health impacts include Sick Building Syndrome (SBS), which describes various nonspecific signs and symptoms that evidently link to the overall IEQ in an indoor environment. The symptoms, for example headache, respiratory irritation and distress, dizziness and fatigue, are usually relived while away from the building (Burge, 2004), therefore it is regarded to be induced by indoor environmental stressors. Indoor factors including ventilation system type, lighting, indoor chemicals and biological factors have been found to be potential inducers of SBS (Seppanen and Fisk, 2002, Takigawa, Wang et al., 2009). Hitherto, neither the specific causal factors nor an indication of a particular disease have ever been discovered.

Long-term health impacts in relation to poor IEQ are classified as Building Related Illness (BRI), which refers to adverse health effects with evidential linkages between environmental factors and illnesses (Seltzer, 1994). Legionnaires' disease, tuberculosis and dermatitis are examples of BRI caused by transmissible pathogens, fungi and air pollutants found in indoor environments (Menzies and Bourbeau, 1997).

A number of studies have evaluated the health impacts of indoor conditions on occupant's health at home. Ahrentzen, Erickson et al. (2016) examined 53 apartment units with energy retrofits and found that improvement in thermal conditions correspond to self-reported improvement of general quality life, general health, emotional distress and sleep. Földváry, Bekö et al. (2017) addressed the health concerns of energy renovations in residential buildings as higher prevalence of SBS and increased levels of formaldehydes (HCHO) and volatile organic compounds (VOCs) were found after building retrofit.

It is notable that some aspect of IEQ, specifically IAQ, can sometimes trigger adverse health effects, even death, without being noticed by human sense. Acute health effects imposed by air pollutants include lung cancer caused by prolonged exposure to radon (Rn) in building materials (Catelinois, Rogel et al., 2006), encephalopathy or death caused by acute carbon monoxide (CO) poisoning (Huang, Peng et al., 2020), etc. Many of these health risks inflicted by poor IAQ are accumulative and delayed, making it difficult to be discovered by sense straight away.

Recognizing the subtle yet concerning health effects of poor IEQ, it is unequivocally that IEQ assessment is fundamental to maintaining a healthy indoor environment by identifying the underlying problems before it is too late.

2.1.2. Effects on productivity

Effects of poor IEQ on productivity have been well-established. Substandard IEQ can lead to absenteeism and presenteeism – working with a reduced productivity due to health problems or distraction (Johns, 2010). A cross-sectional study in Japan found the monetary value imposed by absenteeism and presenteeism was $520 and $3055 per person per year (Nagata, Mori et al., 2018). Fisk, Black et al. (2012) estimated that the annual economic benefits of $13 billion to $38 billion could be achieved across the United States simply by increasing the minimum ventilation rate from 8 L/s to 10–15 L/s, which far exceeded the additional energy cost.

Compared with workplaces, effects on productivity at home have rarely been investigated. Jamaludin, Keumala et al. (2014) conducted a post-occupant evaluation (POE) on the satisfaction and perception of indoor environment with bioclimatic design strategies, with productivity reported to have increased due to improved indoor comfort. Strom-Tejsen, Zukowska et al. (2016) examined the effect of bedroom air quality on next-day performance and concluded that the ability to concentrate and logical thinking improved significantly when carbon dioxide (CO_2) level was lower during sleep.

Even though the effects of poor IEQ on productivity are not as dangerous and life-threatening as the health impacts, it nevertheless has great influences on business and economy. Having IEQ assessment to identify problematic indoor parameters can be beneficial by improving productivity and minimizing building energy consumption.

2.2. IEQ influencing factors

Many factors have been identified to have effects on occupant's satisfaction and productivity. Influencing factors may include building features like indoor climate, air quality, visual comfort, noise, sound privacy, disturbance, interruptions, layout, views and biophilia, model of ventilation, control over the environment and building maintenance (Feige, Wallbaum et al., 2013, Al Horr, Arif et al., 2016); or individual characteristics like gender, age and job satisfaction (Frontczak and Wargocki, 2011).

Kim and de Dear (2012) classified IEQ factors into three categories:

i. Basic factors: minimum requirement that occupants expect them to be fulfilled. Attaining the standard does not necessarily enhance the satisfaction but under-performance can cause dissatisfaction.
ii. Bonus factors: contrary to basic factors, bonus factors have strong positive effects on satisfaction. Under-performance does not necessarily incur displeasure.
iii. Proportional factors: performances of these factors proportionally affect occupant's satisfaction.

Based on a total of 43,021 occupants' surveys from 351 office buildings in Center for the Built Environment (CBE) database, researchers further identified temperature, noise level, amount of space, visual privacy, adjustability of furniture, colour and textures, and workspace cleanliness as the basic factors, air quality, amount of light, visual comfort, sound privacy, ease of interaction, comfort of furnishing, building cleanliness and building maintenance as proportional factors and none for bonus factors. Basic factors like amount of space, visual privacy and noise level also received higher ranks than proportional factors for their impacts on overall IEQ satisfaction (Kim and de Dear, 2012).

On the other hand, IEQ influencing factors and their impacts on occupants in residential settings may be different from those in workplace. Ho, Leung et al. (2004) developed an assessment framework for healthy apartment buildings in Hong Kong, with key environmental quantities including density, air, light, noise, thermal comfort, drinking water, waste and cleanliness. Cho, Lee et al. (2011) evaluated the importance of IEQ factors at home based on a survey of occupant's perception and expert's opinions. It was found that experts viewed illumination, air and noise attributes more important factors for IEQ, while occupants prioritized noise, illumination and facility conditions instead. LEED green building certification program evaluates the IEQ aspect of residential buildings based on air quality (ventilation, combustion venting, garage pollutant protection, radon-resistant construction, air filtering, and environmental tobacco smoke) and compartmentalization. Table 2.1 summarized some factors that influence occupant's satisfaction (Al Horr, Arif et al., 2016). It is by no mean an exhaustive list but an indication of the many different factors that affect occupant's satisfaction to each IEQ aspect.

To provide a holistic understanding of IEQ in enclosed area as a foundation for the development of IEQ model, this section reviews individually the major IEQ influencing factors that affect occupant's comfort and satisfaction. To achieve an acceptable indoor environment, it is essential that both individual IEQ aspects and overall IEQ are at satisfactory level (ASHRAE, 2016). Four principal environmental aspects, namely thermal comfort, IAQ, visual and aural environment, are explored. The interconnections between factors and the space- and occupant- specific prioritization of factors are also discussed to apprehend the complexity of determining overall IEQ.

Table 2.1 Factors that influence occupant's satisfaction to each IEQ aspect (Al Horr, Arif et al., 2016)

Category	Influencing factors
IAQ	Air temperature (T_a), relative humidity (RH), air movement (v_a), level of air pollutants, ambient air quality, ventilation mode/ system, ventilation rate, building materials, human activity
Thermal comfort	T_a, mean radiant temperature (T_{rad}), RH, v_a, outdoor climate, human variables (clothing value (I_{cl}), metabolic rate (M), posture, race, age and gender, body weight, psychological perception, expectation, adaptation)
Lighting & daylighting	Illuminance level, daylight and artificial light ratio, solar radiation and altitude, color, contrast, glare, window access, window size, window orientation, outside temperature, season and time, human behavior
Noise & acoustics	Magnitude of sound, indoor and outdoor source, building envelope, design and material, layout
Office layout	Work process, task, size of workspace, organizational culture, national culture
Biophilia & view	Views of nature and greenery, indoor biophilia feature, artwork
Look & feel	Indoor aesthetics design, color, shape, texture, spatial shape

2.2.1. Thermal comfort

Thermal comfort is defined as “the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation” (ASHRAE, 2017, p. 3), which is a subjective condition for humans. Thermal comfort is the predominant aspect of IEQ to be studied in residential buildings. Andargie, Touchie et al. (2019) identified 81% of single-domain IEQ studies at home were about thermal comfort, with IAQ taking up 9% and the rest shared by aural and visual comfort. In office, thermal comfort is one of the most important parameters of IEQ as it greatly affects productivity, and has a direct impact on building energy consumption (Al horr, Arif et al., 2016). Thermal comfort discusses about the many factors that influence one’s thermal experience, which include environmental factors like T_a, T_{rad}, RH and v_a, and occupant’s characteristics like M, I_{cl}, sociological status and adaption. The combined effects of these objective and subjective factors can be seasonal, occupant- and space- specific.

Thermal comfort of an indoor environment is often evaluated with respect to thermal sensation, thermal neutrality and thermal acceptability. ASHRAE (2017) defines thermal sensation as a “conscious subjective expression of thermal perception of the environment”. While thermal sensation contains certain extent of subjective elements, for example behavioural adaption (de Dear and Brager, 1998), it is generally recognized as an objective expression of the direction and magnitude of sensory response to surround thermal environment, which is largely influenced by six factors: T_a, T_{rad}, RH, v_a, M and I_{cl} (Fanger, 1970). A seven-point thermal sensation scale (-3: Cold, -2: Cool, -1: Slightly cool, 0: Neutral, +1: Slightly warm, +2: Warm, +3: Hot) was therefore developed to quantify occupant's thermal sensation by relating to the aforementioned factors. Thermal sensations can be directly determined through field survey with building occupants (TSV) or estimated by thermal comfort model based on measured environmental parameters.

Thermal neutrality on biological level describes a state that heat generated by metabolism is dissipated and heat balance is achieved (Hey, 1975). It is used to represent a state which occupant's thermal sensation is neutral (0). By exploring the relationship between TSV and T_a, neutral temperature (T_n) can be obtained. Thermal sensation and neutrality can help building engineers understand the perception of an thermal environment, however, using thermal neutrality to evaluate the performance of an enclosed area may not be the most suitable as occupants have been found to prefer a non-neutral sensation (van Hoof, 2008). It has been discovered that thermal sensations besides -1, 0 and +1 were also considered as thermally acceptable (Han, Zhang et al., 2007).

Thermal acceptability describes the percentage of occupants who find a thermal condition acceptable, which is a more straight-forward way to assess a thermal environment. It can be evaluated using a continuous or seven-point scale from -3: very dissatisfied to +3: very satisfied (ASHRAE, 2017), or estimated by thermal comfort model based on established thermal sensation–acceptability relationship. An environment with substantial majority of occupant accepting its thermal condition is regarded as thermal acceptable environment. Thermal acceptance on the other hand depends on psychological factors, expectation, control, etc. (Indraganti, 2010). In non-uniform condition, thermal acceptability was found to be better in describing thermal comfort than thermal sensation (Zhang and Zhao, 2008).

2.2.2. Indoor air quality

Unlike other IEQ influencing factors that rarely trigger adverse health effects unless in extreme and perceptible conditions, poor IAQ can lead to a number of serious health consequences, even death, without being noticed. Susceptibility to indoor air pollution depends on various factors including meteorological, demographic and socio-economic reasons (WHO, 2000). As IAQ discusses about the influences of perceived air on health and comfort, it is not necessary for a person being affected by indoor air pollution to be dissatisfied with the IAQ or the other way around, and an IAQ accepted by occupants does not always suggests a healthy IAQ. Since the health consequences of indoor air pollution are dire, building engineers must ensure an IAQ that can secure both comfort and health of general public.

When IAQ is discussed, people usually refer to one particular parameter: CO_2. CO_2 is mainly generated by building occupants and diluted by mixing with outdoor air, therefore it is considered a good surrogate to represent the occupant load and the ventilation efficiency of an environment. Normal range of indoor CO_2 (350–2,500ppm) is not considered to be a direct health risk for occupants, but evaluated CO_2 was found to be positively associated with increased prevalence of SBS symptoms including headache, fatigue and other respiratory symptoms (Seppänen, Fisk et al., 1999). Apte, Fisk et al. (2000) also found significant dose-response relationships between dCO_2 (indoor minus average outdoor CO_2) and a number of SBS symptoms, but the authors concluded that the relationships did not suggest direct causal linkages, with CO_2 being correlated with other indoor pollutants that may cause these symptoms. Causal relationships between indoor CO_2 level and health symptoms remain inconclusive, nevertheless, its capacity as a surrogate indicator for IAQ is universally recognized.

Particulate matter (PM) is another dominant indoor air pollutant which can be originated from outdoor environment or generated from indoor activities like cooking, smoking and building materials (Lee, Guo et al., 2002). Various particle sizes determine the health impacts. The smaller the particle, the deeper it can deposit into the respiratory tract by inhalation, causing severe effects like respiratory distress, asthma, cardiovascular diseases, lung cancer and ultimately, death (WHO, 2013). PM is considered as a surrogate indicator for filtration performance of building ventilation system (Mui, Wong et al., 2006), therefore evaluation of IAQ in premises served by mechanical ventilation and air-conditioning system (MVAC) usually includes the assessment of PM. In residential settings where split-type and window type air-con are employed, PM instead represents the intensity of PM-generating human activity. It has been found that modern high-rise residential buildings generally suffer higher indoor PM levels than office. With a fair amount of time people spent at home, PM exposure at home contributes to a majority of personal integrated exposure to PM (Yang, Lau et al., 2019).

Volatile organic compounds (VOCs) are wide range of organic compounds that have high vapour pressure at room temperature, therefore having a high volatility and easily evaporate or sublimate. VOCs have long been found to be associated with adverse non-acute health effects such as SBS and sensory irritation (Andersson, Bakke et al., 1997). Some VOCs are linked to severe health consequences like myeloid leukemia and lymphocytic leukemia by benzene exposure (Snyder, 2012), and various kind of cancers by prolong exposure to formaldehyde (Swenberg, Moeller et al., 2013). Since there may be numerous kinds of VOCs in an indoor environment, for simpler and faster reporting purpose, the term total volatile organic compounds (TVOCs) is generally adopted to describe the indoor exposure to total concentration of VOCs and to estimate the health risk. TVOCs has been considered as a surrogate indicator for emissions from building materials, ventilation efficiency and high polluting activities (Molhave, Clausen et al., 1997).

Besides the surrogate indicators described above, many parameters can pose threats to occupant's health if the level is high. For example, the concentration of airborne bacteria in air is often measured to evaluate the infection risk. In developing countries which coal and biomass fuels are still used as energy sources, CO poisoning is one of the major causes of death from poor IAQ (Smith, Mehta et al., 2004). Ozone (O_3) generated by indoor sources like printers and air cleaners is another concerned air pollutant as long-term exposure to high O_3 level can cause permanent damage to lung and various kinds of respiratory dysfunctions (Sheffield, Zhou et al., 2015). Rn exposure is also a subject of matter for IAQ as it can be found in soil and building materials. Though susceptibility to Rn varies from person to person, it has been confirmed that prolonged low and moderate Rn exposure increase the risk of lung cancer (Zeeb, 2009). In addition to air pollutants generated from indoor sources, pollutants originated from outdoor sources, for example nitrogen oxides (NO_x) and sulphur dioxide (SO_2), are sometimes monitored as they can infiltrate into enclosed environments through windows, door openings and ventilation systems.

2.2.3. Visual comfort

Visual comfort can be defined as "a subjective condition of visual well-being induced by the visual environment" (BSI, 2018). Some parameters have been found to influence visual comfort, including glare, solar radiation, daylight, illuminance level, access to exterior view, uniformity of lighting, abundance of daylight hours, direct sunlight hours, controllability, perceived spaciousness and quality of light in rendering colors (Carlucci, Causone et al., 2015).

Lightings in dwellings are typically divided into: i) ambient lighting, which describes the light required for basic activities; ii) task lighting, the visual requirement for specific functional task; and iii) accent lighting, which provides visual relief and attraction (Holton, 2012). In residential settings, as occupants have more control over the lighting than in office (Galasiu and Veitch, 2006), they may accept a visual environment with illuminance level lower than comfort threshold. Lai, Mui et al. (2009) also found that among the four major IEQ factors, visual environment was less considered, and that overall acceptance would not increase further when horizontal illuminance reached 50lux. It can be interpreted that as long as the ambient lighting is sufficiently provided in an apartment, residents can easily adjust the lighting level with additional task light for specific task, making visual comfort trifling among other IEQ factors in residential settings.

On the contrary, due to the functionality of premises, amount of lighting in workplace is crucial to occupant's well-being and productivity. Adequate amount and high quality of light give higher visual satisfaction and comfort, therefore enhance job performance (Lee and Guerin, 2010). In addition to the lighting condition, as office workers have limited control over the visual environment, visual comfort may also be affected by perceived views and environmental conditions. Positive psychological responses were associated to perceived window views and the presence of indoor plants in office. Given no view and plant, occupants showed the highest degree of tension and anxiety (Chang and Chen, 2005). Aries, Veitch et al. (2010) also identified window view type, view quality and social density to have significant influences on physical and psychological discomfort. These discomforts can subsequently affect worker's sleep quality at home.

Given so many subjective parameters that can influence visual comfort, to simplify the assessment procedure, the evaluation of visual performance of an environment is often achieved by an index focuses on only one of the above-mentioned factors that can be objectively assessed, for example glare or the amount of light (Carlucci, Causone et al., 2015).

2.2.4. Aural comfort

Aural comfort can be described as the provision of an acoustic environment that protects occupants from noise and annoyance, and is acceptable for the purpose of the premises. Prolonged exposure to high-frequency noise, both continuous and impulse noise, can induce hearing impairment (Lie, Skogstad et al., 2016), which may be seen in industrial environments. In residential and office environment, unwanted noise can be harmful to psychological health, resulting in nervousness, loss of focus and reduced productivity (Mujan, Anđelković et al., 2019). With growing trend of open-plan office and studio flats, it is important to maintain an aural environment that occupants find comfortable and desired for various activities.

Building design plays an important role in maintaining an acceptable acoustic environment. Noise is transmitted from outdoor, for example traffic, into the indoor environments through building façade and windows. To reduce such transmission, building structure and building envelope shall be designed to enhance sound reduction property to minimize outdoor noise (Al Horr, Arif et al., 2016). Indoor noise can be originated from building system and activities like conversation and use of office equipment. These inconsistent annoyances greatly lower worker's concentration and work performance (Banbury and Berry, 2005). Internal noise can be minimized with the use of partition, sound insulation and better layout. Despite the impacts of noise on productivity, research into aural comfort in relation to IEQ is lacking. Evaluation of acoustic environment is usually attained by simply measuring the noise level to ensure an acceptable noise level as required by building regulations and occupational standards.

2.2.5. Interconnections and interdependency between factors

While the above-mentioned factors seemingly describe IEQ from entirely different aspects, research has shown a complex relationship between individual factors which produces combined effects on overall IEQ satisfaction. Interaction between factors can be defined as "the combined effect on building occupant of two or more environmental factors or their aspects" (ASHRAE, 2016, p. 3). These effects can be from actual physical influences of different aspects on each other, or from the alteration of occupant's psychological perception on environmental conditions with the given stimulation. Interaction among IEQ factors can be classified as independent, additive, synergistic, antagonistic, prophylactic, cumulative and unintended. Table 2.2 shows the explanation of each interaction that can be found in indoor environments. As the combined effects vary among different types of occupants, and the type and intensity of interactions differ among various circumstances, it is recognized as one of the limits to existing building standards and guidelines (ASHRAE, 2016).

Table 2.2 Explanation of interconnections between indoor environmental factors (ASHRAE, 2016)

Interaction	Explanation
Independent	Effects of environmental factors are independent of each other
Additive	Each factor has its own effect, with joint effect being the sum of effects of all factors
Synergistic	Each factor has its own effect, with joint effect being greater than the sum of effects of all factors
Antagonistic	Each factor has its own effect, with joint effect being less than the sum of effects of all factors, or even cancel out the effects of each other
Prophylactic	Factors are maintained as preventive measures against adverse impacts on health and productivity
Cumulative	Effects of factor are cumulative over prolonged exposure
Unintended	Factors are maintained with the intention to improve one of the aspects of IEQ, but in turn producing negative effects on another

Interconnection between factors can be classified into different orders. First-order interaction describes the interactions among factors of same environmental aspect, for example the combined effects of indoor temperature and clothing insulation in free-running buildings, resulting in different thermal responses to perceived thermal environment as described by Fanger's PMV/PPD model (de Dear and Brager, 1998). Other first-order interactions between factors have been discussed in previous sub-chapters regarding the four principal environmental aspects.

Second-order interaction concerns about the interaction between different aspects, which is more complex than first-order interaction. For example, significant interactions between visual and thermal environment has been found in literature. Chinazzo, Wienold et al. (2019) found that daylight substantially influenced thermal comfort and acceptability, but had no effects on thermal sensation and preference. They further confirmed that daylight could only affect thermal perception psychologically, not physiologically, in contrast to the conclusion drawn by te Kulve, Schellen et al. (2016) that light could affect thermoregulation and therefore alter thermal sensation and comfort. Alternatively, thermal environment also affects visual perception. te Kulve, Schlangen et al. (2018) investigated the interaction between perception of light and temperature and found a positive relationship between visual and thermal comfort, i.e. when temperature was perceived as comfortable, the visual conditions were also considered as more comfortable. Preferred correlated color temperature and ambient temperature were also found to be positively correlated.

Effects of thermal environment on perceived IAQ were also examined. A number of studies have found that high air temperature and humidity negatively affect IAQ acceptability. Fang, Wargocki et al. (1999) found from a controlled experiment that levels of indoor air enthalpy had significant negative effects on acceptability of perceived air quality. Lan, Wargocki et al. (2011) also confirmed such negative relationship between thermal comfort sensation and perception of air quality from field studies.

Interaction between thermal and acoustic environment was also investigated. High noise level was found to cause a poorer thermal perception (Tiller, Wang et al., 2010). As for the effects of temperature on aural comfort, conflicting conclusions were made. Some found that perception of noise was not affected by ambient temperature (Tiller, Wang et al., 2010); others like Nagano, Nagano et al. (2001) found that thermal condition significantly affected noise sensation. Huang, Zhu et al. (2012) discovered that when thermal environment was satisfactory, occupants regarded a higher noise level acceptable, suggesting that IEQ factors could even offset each other's effect on overall IEQ.

The interaction between factors, despite that complexity, can sometimes be identified and factored in to minimize the discrepancies between occupant's actual responses and model predictions. For instance the aforementioned disparity in thermal comfort was improved by the adaptive thermal comfort model developed specifically for buildings with natural ventilation, where adaptive measures are expected and therefore included in the assessment (de Dear and Brager, 1998). Others attempted to use weighting schemes, usually in form of linear regression model, to relate overall IEQ with individual factors (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Cao, Ouyang et al., 2012). However, due to the intricacy of interaction between IEQ factors, IEQ modellings are usually discussed with a limited number of four principal environmental aspects, i.e. thermal comfort, IAQ, aural and visual comfort (Heinzerling, Schiavon et al., 2013).

2.2.6. Prioritization of factors on overall IEQ

A prioritization of factors (i.e. perceived importance/ ranking) on overall IEQ has been observed to vary among building and occupant types (Sakhare and Ralegaonkar, 2014). Frontczak and Wargocki (2011) reviewed the ranking of importance of factors on overall IEQ from various field studies based on subjective responses, discovering that in general thermal comfort was ranked more important than aural comfort and IAQ, with visual comfort being the least important. Field research arrived later also showed the same ranking in different types of indoor environments (Cao, Ouyang et al., 2012, Huang, Zhu et al., 2012).

Besides a general prioritization, preferences for specific IEQ factor were observed in buildings with different usages. For example, a quiet acoustic environment was deemed more important than other aspects in learning environment (Lee, Mui et al., 2012). Thermal environment was less concerned than air quality and aural comfort in commercial buildings, but the case was reversed in residential settings (Lai and Yik, 2009).

Alternatively, even for buildings with similar usage, ranking of factors could vary among occupants of different demographics. In Lai and Yik (2009) mentioned above, it was found that aural comfort was more important than IAQ for lower income group, while high income people preferred better IAQ over better acoustic environment. Choi, Aziz et al. (2009) suggested that both genders ranked IAQ and thermal comfort the most important; female valued visual comfort more than aural comfort, but male concerned more about aural than visual environment instead. Age, nationality, job nature, job satisfaction and work space also strongly affected the perception of indoor environment in office (Haghighat and Donnini, 1999), contradicting to findings by Erlandson, Cena et al. (2003) and Newsham, Brand et al. (2009), in which no significant influence of occupant's characteristics on environmental satisfaction was found.

Frontczak and Wargocki (2011) concluded from the review on influences of factors on IEQ that, despite significant difference on perceived importance was found to depend on a number of environmental and occupant's characteristics, no general conclusion on ranking of factors could be formulated due to the inconsistency. While it is important to model overall IEQ satisfaction with individual factors for the purpose of improving the indoor environment and set up remediation strategies, it is nevertheless challenging due to the fact that individual impacts are not systematic.

2.3. Assessment methods and models

There are many different ways to assess an indoor environment. Majority of existing literature investigate the indoor environment based on single-domain method – studying occupant's satisfaction on one particular environmental aspect, or more than one aspect, separately. Research into multi-domain environmental quality, i.e. the combine effects on overall IEQ, is on the other hand rather limited (Schweiker, Ampatzi et al., 2020).

Single- and multi-domain evaluations can be achieved by subjective and objective assessment methods. Subjective assessment considers building user's feelings and comfort inside the premises the prime interest, regardless the actual physical environmental conditions they are experiencing (Heinzerling, Schiavon et al., 2013). It utilizes surveys to collect occupant's responses and satisfaction towards perceived environment, which is deemed the simplest and most straight-forward way to evaluate IEQ (Nicol and Wilson, 2011). However, subjective surveys sometimes result in diverse or even contradicting opinions for similar physical environment. Operating buildings based only on occupant's satisfaction may also create undesired energy wastage (Heinzerling, Schiavon et al., 2013). Difficulties in finding a representative period for measurement, interpreting the results and asking the appropriate questions were suggested to be the drawbacks for relying only on subjective assessment for IEQ evaluation (Nicol and Wilson, 2011).

Alternatively, objective assessment methods, for instance conducting field measurements of physical environmental conditions without evaluating occupant's satisfaction, can avoid the problems of subjective nature of results and lack of universal judgement (Asadi, Mahyuddin et al., 2017). Nevertheless, time and monetary cost for field measurements are often expensive. Constant calibration of measurement instrument is also needed to ensure data quality. Judgement on representative measurement periods, locations and environmental parameters, and interpretation of results require experts and professionals, while monitoring and analysing large amount of data may not be practical (Heinzerling, Schiavon et al., 2013).

In the following sub-chapter, different kinds of subjective and objective assessment methods for thermal comfort, IAQ and overall IEQ are reviewed. Thermal comfort is focused as it is often the most concerned and heavily investigated factor of IEQ. It also dominantly affects the building energy consumption. IAQ is also paid attention to as it is the second-most investigated topic in IEQ, and in particular as it is health-related, which in addition to be assessed by subjective sense, shall also be investigated objectively based on health standard. Subjective sensation on IAQ can ensure comfort, but more are needed to be done to protect the occupants from poor IAQ. The pros and cons of each method are discussed and the research gaps in the field are identified. The research needs for developing simpler, cost-effective, accurate and comprehensive assessment approaches for indoor environment evaluation are explicated.

2.3.1. Thermal comfort

Thermal comfort is the most discussed IEQ aspect in the field as it has a significant impact on productivity and health. Energy implication of heating, ventilation, and air conditioning (HVAC) system for maintaining a comfortable thermal environment is also one of the biggest concerns for building engineers (Perez-Lombard, Ortiz et al., 2008) as the system accounts for about 25% of the total building energy load (OECD, 2016).

Assessment methods

Thermal comfort can be assessed subjectively and objectively. Subjective thermal comfort assessment involves asking the occupants a set of questions regarding the thermal sensation, thermal preference, thermal satisfaction and/ or thermal acceptance. It allows us to obtain occupant's thermal comfort perception directly. ASHRAE (2017) details the subjective survey criteria that substantial response rate is required to make a representative sample size. Subjective thermal survey is conducted through a scale – thermal satisfaction with a scale from "very dissatisfied" to "very satisfied"; thermal acceptability with a continuous or seven-point scale from "very unacceptable" to "very acceptable"; and thermal sensation with ASHRAE seven-point sale of -3: Cold, -2: Cool, -1: Slightly cool, 0: Neutral, +1: Slightly warm, +2: Warm and +3: Hot. In practice, some may prefer to use direct "yes"/ "no" questions when asking about thermal acceptance and satisfaction. Regarding thermal sensation "-1", "0" and "+1" as thermally acceptable, "-3", "-2", "+2" and "+3" as unacceptable, is also a common practice. Thermal preferences for indoor temperature and air velocity are also used, especially in adaptive thermal comfort study such as ASHRAE RP-884 database (de Dear and Brager, 1998). Beside, to identify the source of problem of thermal discomfort, additional questions may aid the formulation of improvement strategies.

In cases which the involvement of occupant's thermal response is not feasible (for example, new buildings), objective measurements of physical thermal environment can be done to indirectly predict occupant's responses through pre-determined thermal comfort models, which are established previously from subjective-objective studies that relate subjective responses to objective physical environmental conditions.

Prediction model

PMV model proposed by Fanger (1970) is currently one of the most highly cited indoor thermal comfort models in the field. It has been the basis of building standards like ANSI/ASHRAE 55-1992 and ISO 7730:1994. PMV model is an empirical comfort equation developed based on the consideration of steady-stage heat balance between body and thermal environment. Given the assumption that thermal sensation is driven by only physiological stimulations, based on the experimental results collected from 1296 test subjects conducted in a controlled environmental chamber, Fanger related four indoor parameters: indoor air temperature (T_a), mean radiant temperature (T_{rad}), relative humidity (RH) and air velocity (v_a), and two occupant's criteria: metabolic rate (M) and clothing value (I_{cl}), to ASHRAE seven-point thermal sensation scale. Equations 2.1–2.5 shows the method for calculating the PMV suggested by ISO 7730.

$$PMV = \left[0.303e^{-0.036M} + 0.028\right] L \qquad -(2.1)$$

$$L = (M-W) - 3.05\times10^{-3}\cdot[5733-6.99(M-W)-p_a\cdot RH]$$
$$- 0.42[(M-W)-58.15] - 1.7\times10^{-5}M\cdot(5867-p_a\cdot RH)$$
$$- 0.0014M\cdot(34-T_a) - 3.96\times10^{-8}f_{cl}\cdot\left[(T_{cl}+273)^4\right]-(T_{rad}+273)^4\Big]$$
$$- f_{cl}\cdot h_c\cdot(T_{cl}-T_a) \quad -(2.2)$$

$$T_{cl} = 35.7 - 0.028(M-W)$$
$$- I_{cl}\cdot\left\{3.96\times10^{-8}\cdot f_{cl}\left[(T_{cl}+273)^4-(T_{rad}+273)^4\right]+f_{cl}\cdot h_c(T_{cl}-T_a)\right]\Big\} \quad -(2.3)$$

$$h_c = \begin{cases} 2.38\times(T_{cl}-T_a)^{0.25}, & 2.38\times(T_{cl}-T_a)^{0.25} > 12.1\times\sqrt{v_a} \\ 12.1\times\sqrt{v_a}, & 2.38\times(T_{cl}-T_a)^{0.25} < 12.1\times\sqrt{v_a} \end{cases} \quad -(2.4)$$

$$f_{cl} = \begin{cases} 1.00+1.290I_{cl}, & I_{cl}\le 0.078 \\ 1.05+0.645I_{cl}, & I_{cl}>0.078 \end{cases} \quad -(2.5)$$

While knowing the thermal sensation without understanding whether occupants are satisfied with the thermal condition or not does not help with improving the indoor environment. Therefore, Fanger further related PMV with PPD, which quantitatively predicts the percentage of people being dissatisfied with the thermal condition. It is assumed that people with thermal sensation “-3”, “-2”, “+2” and “+3” are thermally dissatisfied and thermal dissatisfaction is symmetric. PPD can be expressed by Equation 2.6. Figure 2.1 exhibits the graphical presentation of the correlation between PMV and PPD. In practice, comfort zones for acceptable range of the four environmental parameters given by the two occupant’s criteria are usually adopted to determine environmental conditions that meet with 80% thermal acceptability (based on 10% whole body thermal discomfort given by PMV/PPD model and 10% local body thermal discomfort), with approximately 5% of population being thermally dissatisfied even at PMV = 0.

$$PPD = 100 - 95e^{-0.03353PMV^4 - 0.2179PMV^2} \quad \text{– (2.6)}$$

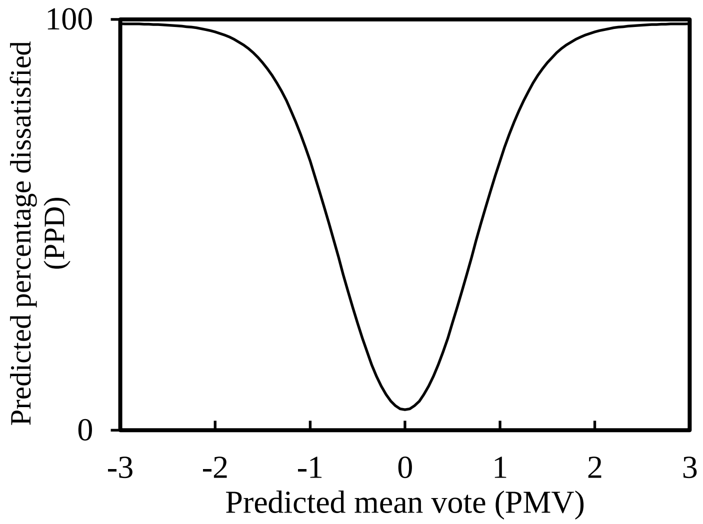


Figure 2.1 Correlation between predicted mean vote (PMV) and predicted percentage dissatisfied (PPD)

Discrepancies between PMV/PPD model predictions and thermal sensation and dissatisfaction from field surveys have been found in many studies covering various kinds of indoor environments. Humphreys (1978) investigated the effect of prevailing outdoor climate on T_a, discovering that thermal sensation and T_n strongly depended on outdoor mean temperature. For free-running buildings (building without heating or cooling), 94% of T_n was associated with the variation of outdoor mean temperature, suggesting that outdoor climate could strongly influence occupant's thermal comfort especially in building with natural ventilation.

Brager and de Dear (1998) also challenged the universal applicability of PMV/PPD model as it mostly ignored the contextual influences that could alter thermal experience. Given that, in addition to conventional belief of physical and physiological interactions between occupants and the thermal environments, social, cultural and personal (i.e. adaptation) factors have been found to affect thermal comfort, especially in buildings with natural ventilation, they proposed an adaptive hypothesis to include occupant adaptive behaviour into thermal comfort prediction (de Dear and Brager, 1998). This belief acknowledges the involvement of occupants in thermal interaction with the environment through change in behaviour (e.g. change in position and clothing insulation), expectation and adaption, and eventually changes the thermal preferences. Three thermal adaptations were categorized: i) behavioural adjustment, which describes personal, technological and cultural actions taken by a person in order to govern body's thermal balance; ii) physiological adaptation, which refers to alteration to the physiological responses upon prolonged exposure to certain thermal condition, either genetically adapts to the climate which takes generations, or acclimatizes to the thermal conditions over months and years of exposure; and iii) psychological adaptation, which includes the change in perception and reaction to thermal condition due to past experience and expectations (de Dear and Brager, 1998).

Assuming that thermal adaptation could be obtained from field data, de Dear and Brager (1998) developed the adaptive thermal comfort model based on RP-884 database, which contained 21,000 standardized thermal comfort field data from a wide range of places covering a spectrum of climatic zones. It was found that for buildings with centralized HVAC system, predictions by PMV/PPD model and adaptive model were very close, suggesting that some of the adaptation behaviour like clothing and air velocity adjustment were well accounted for in PMV/PPD model. On the other hand, in buildings with natural ventilation, predictions by PMV/PPD model and adaptive model varied differently from each other (slope of adaptive model was twice the one in PMV/PPD). It was proposed that psychological adaptation, for instant expectation and habituation, was a probable explanation for such discrepancies. Adaptive thermal comfort model has been implemented in ANSI/ASHRAE 55-2004 and 55-2010 for natural ventilated buildings and EN 15251 for mixed-mode buildings under natural ventilation.

van Hoof (2008) summarized in his review the discrepancies between actual field data and predictions by the PMV/PPD model, and suggested that prediction can be improved by validating the PMV/PPD model, better specifying the model parameters and incorporating more influencing parameters like outdoor thermal condition.

Recognizing the inadequacy of the PMV/PPD model, some adjustments and modifications have been proposed to improve the accuracy, reliability and application range of the model, for example using PMV_e to include the thermal expectancy of occupants, which aimed at expanding the PMV model to non-air-conditioned buildings in warm climate (Fanger and Toftum, 2002). In addition to lowering the metabolic rates of activities in warm environments to adjust to human body mechanism, an expectancy factor, *e*, was introduced to account for the expectation of occupants due to adaption to warm climate. *e* was believed to depend on the duration of the warm weather over the year. PMV_{new} was also introduced to reduce bias against contributing parameters and to extend the application range of the PMV model (Humphreys and Nicol, 2002). Yao, Li et al. (2009) developed a theoretical adaptive thermal comfort model based on PMV and the "Black Box" theory. The model takes cultural, climatic and social factors into account and incorporates an adaptive coefficient into the PMV model. Adaptive behaviour can thus be related to the experimental results by Fanger, and the differences between measured and predicted mean votes shall be minimized. Langevin, Wen et al. (2013) used Bayesian parameter estimation approach to extend the PMV model to field use. They developed Bayesian thermal sensation, acceptability and preference distributions to formulate a new relationship between PMV and PPD. Wong, Mui et al. (2014) presented a Bayesian approach to refine Fanger's model with the use of field survey data. The approach allows systematic updates on our current beliefs about thermal dissatisfaction. Based on the best information available (i.e. existing models and field survey data), it evaluates the statistical importance of field data with a chosen target sample size and an acceptable error value. By integrating the PMV model with the adaptive approach, Marino, Nucara et al. (2015) developed a subjective-adaptive thermal comfort model for predicting thermal sensation. This approach, which uses a multi-agent system to survey user thermal preferences and adapts itself to user choices, is able to achieve personalized thermal comfort controls.

Alternatively, thermal comfort can be assessed individually. In fact, the number of personal comfort models is on the rise. Personal thermal comfort model is a data-driven approach to assess thermal comfort by predicting individual's responses instead of averaging the thermal comfort of a group of occupants. Individual's thermal comfort data are directly fed back to the system with the help of IoT, and with the additional personal data, machine learning algorithms, such as logistic regression techniques, support vector regression and Bayesian network are employed to train a personal comfort model (Hamzah, Gou et al., 2018). With six different machine learning algorithms (Classification Tree, Gaussian Process Classification, Gradient Boosting Method, Kernel Support Vector Machine, Random Forest, Regularized Logistic Regression), Kim, Schiavon et al. (2018) showed that personal comfort models gave much better prediction performance than conventional PMV and adaptive thermal comfort models. Although a personal comfort model has its data-driven flexibility, its machine learning approach requires an expensive feedback and sensing system for identifying actual individual's preferences. Besides, it is not feasible for buildings in design stages.

Moreover, human body thermal sensation and comfort can also be modelled by mimicking human thermal regulation by simulating convective heat transfer between body segments and tissues using thermal manikin. Unlike the PMV/PPD model and adaptive thermal comfort model that can only predict thermal comfort under steady-state thermal conditions, thermoregulation models are able to simulate transient and spatially non-uniform environmental conditions, therefore identifying local thermal discomfort (Zhang, Huizenga et al., 2005). Famous ones include Stolwijk's 25-node model of thermoregulation (Stolwijk and Hardy, 1966) and the Berkeley Comfort Model (Huizenga, Hui et al., 2001). Nevertheless, further discussions regarding personal comfort models and thermoregulation models are not included as these are out of the scope of this study.

While considerable research has been devoted to developing or improving thermal sensation models, far too little effort has been directed towards assessing thermal acceptance. Despite the fact that new Bayesian approaches have been developed for the improvement of PMV/PPD representation, e.g. Langevin, Wen et al. (2013) Wong, Mui et al. (2014), the conventional PMV/PPD model is still the primary tool for assessing the thermal acceptance of occupants in most thermal comfort research studies.

In spite of everything, attempts to improve PMV/PPD model seem to fail in generalizing the original model in terms of types of environments and occupants. At the moment, PMV/PPD model remains the most generally accepted one due to its simplicity and objectivity, which is especially important and useful for the determination of thermally comfort environment during building design stage. The original PMV/PPD model is still the number one method for thermal comfort evaluation, and is highly recognized and widely adopted in building research and as design reference.

2.3.2. Indoor air quality

Compared to other aspects of IEQ, subjective sensation of IAQ can evaluate comfort, but may not be a good indicator of the health consequences posed by poor IAQ. Pollutants like CO and Rn are colourless, odourless and tasteless, therefore cannot be detected by human senses. Some indoor air pollutants, for instance some VOCs and PM, can certainly make you feel uncomfortable if the levels are high enough to be detected by human senses (WHO, 2013), but prolonged exposure to low levels of these pollutants can still pose negative health effects. WHO (2010) also detailed a number of air pollutants commonly found in indoor environments that are known to be health hazards. Many of them, especially in the VOCs category, can produce carcinogenic effects (cancer-causing effects) on human upon long-term exposure to low concentration through inhalation of particles. Since human sometimes is not a reliable “detector” of poor IAQ, and accumulative effects of long-term exposure to indoor air pollutants are relatively common, assessing IAQ is often done in objective ways rather than subjectively.

Assessment methods

Subjective perceived IAQ assessment involves questionnaires asking occupants to rank the acceptability of IAQ using scales. Objective measurement of representative IAQ pollutants, mainly CO_2, may also be conducted at the same time to identify the associations between satisfaction to IAQ and pollutant levels. Subjective IAQ assessment is usually done to evaluate comfort instead of health hazard, and it is an essential step to identify the acceptability to overall IEQ when IAQ is considered.

Objective IAQ assessment is conducted through field survey of IAQ parameters, ranging from as simple as one parameter, usually CO_2, to more than 10 commonly seen air pollutants, include but not limited to CO, HCHO, lead (Pb), O_3, Rn, and TVOC. It is necessary for building professionals to preliminarily assess the environment in order to identify the representative periods and sampling locations based on educated judgement. It is also essential to ensure the accuracy and sensitivity of measurement instruments by laboratory calibrations (Heinzerling, Schiavon et al., 2013).

Due to the detrimental health impacts of poor IAQ, many places and international bodies have developed standardized IAQ assessment protocols and IAQ standards in order to ensure the provision of up-to-standard IAQ. For instance, China published the "Indoor Air Quality Standard (GB/T18883-2002)" in 2002, which included four physical parameters: T_a, RH, v_a, and fresh air rate, 13 chemical parameters: SO_2, NO_2, CO, CO_2, Ammonia (NH_3), O_3, HCHO, benzene (C_6H_6), toluene (C_7H_8), ethylbenzene (C_8H_{10}), PM_{10}, TVOC and benzo(a)pyrene), one biological IAQ parameter: airborne bacteria count (ABC) and one radioactive parameter: Rn . The government of South Korea has put into effective the "Indoor Air Quality Control in Public Use Facilities, etc. Act" since 2004, which is applicable to most kinds of public indoor places, with two levels of control: mandatory standard covering PM_{10}, CO, CO_2, HCHO and ABC, and recommended standard covering TVOC, NO_2, Rn, asbestos and O_3. Penalty is given to any violation of the mandatory standard.

Some countries, instead of issuing laws and regulations to control IAQ, they set up goals, guidelines and code of practices for controlling IAQ. For example, Finland published

“Indoor Air Guidelines” in 1997 requiring responsible parties to take remediation measures against health hazards caused by poor IAQ. In Germany, IAQ-related problems are managed by building codes. Air pollutants include C_7H_8, styrene (C_8H_8), dichloromethane (CH_2Cl_2), pentachlorophenol (PCP), CO and NO_2 are monitored. Exposure limits shall be of no concern of any adverse health effects, with Guideline value I suggests pollutant value that does not cause adverse health effects under life-long exposure; and Guideline value II gives a concentration that health threats are anticipated especially for vulnerable people like children and elderlies (Seifert, Englert et al., 1999)

As an internationally recognized public health agency, World Health Organization (WHO) also published the “WHO Guidelines for Indoor Air Quality: Selected Pollutants” to provide guidance on reducing health impacts caused by prolonged exposure to indoor air pollutants. This guideline serves as a scientific basis for decision making in environmental and public health management, as well as individual facility design and management. The guideline covers a number of hazardous chemicals such as C_6H_6, CO, HCHO, etc. The indoor sources, toxicities, exposure pathways, health impacts and methods for controlling the levels are detailed in the publication (WHO, 2010).

Hong Kong has started to combat the problem of IAQ way back since 1989. The very first preliminary IAQ assessment conducted in 1990 in 70 air-conditioned offices and street-level shops revealed serious IAQ problems in Hong Kong including poor ventilation and elevated CO_2 and VOCs levels (Liao, Baconshone et al., 1991). The government therefore addressed the health effects, economic impacts and necessary actions to tackle IAQ problems in the “Second Review of the 1989 White Paper on

Pollution in Hong Kong". The "Hong Kong Interim IAQ Guidelines" was proposed in the next year by the Environmental Protection Department (EPD) and the "Indoor Air Quality Management Group" was set up in 1998 for the purpose of planning for IAQ-related policies and management strategies to improve the overall IAQ in Hong Kong.

In 2003, the "Guidance Notes for the Management of Indoor Air Quality in Offices and Public Places (Guidance Notes)", a non-legally binding practical guide for building owners and managers to manage the IAQ of premises, was published. A voluntary "IAQ Certification Scheme for Offices and Public Places (the Scheme)" was also endorsed. The Scheme is a voluntary benchmarking system for offices and public places served by MVAC systems. In order to improve IAQ and promote public awareness, the Scheme put forward two benchmarks of IAQ objectives: Excellent Class – a high-class and comfortable building should have; and Good Class – an IAQ that can provide protection to the public at large.

Unfortunately, despite the efforts by the authority, low participant rate was recorded with a total of 1,871 premises in mid-2020 (51.7% from non-governmental agencies, 41.5% from governmental organizations, 4.1% from semi-public administrative body, 2.7% from educational institutions), suggesting a low incentive in engaging in this certification process. While the Scheme aims at improving Hong Kong's overall IAQ situation by recognizing good IAQ management practices, increasing IAQ complaints have been received over the years, as shown in Table 2.3.

Table 2.3 Indoor air quality (IAQ) complaints received by the government (EPD, 2012, EPD, 2014, EPD, 2017, EPD, 2018)

Type of complaint	2012	2014	2017	2018
Poor ventilation	161	110	285	284
Too high or too low indoor temperature	182	385	467	586
Dust problems	26	70	16	25
Odour	134	114	48	84
Chemicals (e.g. VOCs, HCHO, etc.)	21	14	11	15
Fungi/ mold	17	7	13	1
Non-specific complaint	17	6	30	55
Total	558	706	870	1,050

Drawbacks of the Scheme and reasons for low motivation for participation have been suggested in literatures. One of the major reasons for weak incentive is high implementation cost. Burnett (2005) estimated a total cost of around US$40,000 is required for solely certifying a typical 40-storey office building (Burnett, 2005). With lower certification costs being offered nowadays, resources, manpower and money invested into this voluntary certification process in terms of surveying, result interpretation, calibration and maintenance of instrument, is still high. Given no benefit to the business is guaranteed, the cost can be a burden to small and mid-size enterprise (Wong, Mui et al., 2006). It is also expensive to improve IAQ if the IAQ problems come from the building itself, for example high VOCs emission from building materials, high CO_2 level due to high occupancy or low ventilation rate, etc. It has been estimated that increasing the air change rate (ACH) to enhance ventilation efficiency and lower CO_2 level by 200ppm can lead to 5–10% increase in energy consumption of the ventilation system (Burnett, 2005).

Building professions also doubt the rationale behind the selection of IAQ parameters and the exposure limits. Some parameters like CO_2 do not pose health hazards even the indoor concentration exceeds the exposure limit. Items like T_a, RH and v_a do not directly affect the IAQ but rather the comfort level of occupants. Failing the Scheme does not necessarily imply a bad IAQ (Burnett, 2005). In response to the comments made by the practitioners, the objectives were later reviewed and updated in 2019 based on the latest IAQ guidelines by WHO. Physical parameters including T_a, RH and v_a were removed while mold was added into the 9 existing IAQ parameters. Exposure levels of CO, PM_{10} and Rn were, however, tightened, and short-term exposure levels for HCHO and NO_2 were included. Table 2.4 exhibits the previous and updated IAQ objectives in the Scheme.

Table 2.4 IAQ objectives in IAQ Certification Scheme for Offices and Public Places

Parameter	Unit	Averaging time (hr)	Old objective		New Objective	
			Good Class	Excellent Class	Good Class	Excellent Class
T_a	°C	8	<25.5	20–<25.5	Removed	
RH	%	8	<70	<40-70		
v_a	m/s	8	<0.3	<0.2		
CO_2	ppmv	8	<1,000	<800	1,000	800
CO	ppmv	8	<8.7	<1.7	6.1	1.7
PM_{10}	μg/m^3	8	<180	<20	100	20
NO_2	μg/m^3	8	<150	<40	150	40
		1	-	-	200	100
O_3	μg/m^3	8	<120	<50	120	50
HCHO	μg/m^3	8	<100	<30	100	30
		0.5	-	-	100	70
TVOC	μg/m^3	8	<600	<200	600	200
Rn	Bq/m^3	8	<200	<150	167	150
ABC	cfu/m^3	8	<1,000	<500	1000	500
Mold	-	-	-	-	prescriptive checklist	

In addition, the Scheme is also being criticized for its lack of flexibility in measurement procedures. Technical difficulties and uncertainties of the whole IAQ assessment process have also been reported. Wong, Mui et al. (2006) pointed out that details like correction of survey data for alternative measurement protocols and criteria for sampling density determination were not specified. Lengthy sampling period, high sampling point density and operating measurement instruments may be a nuisance to building occupants during the assessment period. Alternatively, to avoid undesired disturbance, some new offices opt to conduct the certification process before the tenants move in, which cannot represent the actual IAQ situation caused by human activities during occupancy period.

A number of studies have provided alternative sampling schemes with shorter measurement period and simplified procedures, which were proven to be able to give accurate assessment results with less resources invested. Mui and Wong (2004) and Mui, Wong et al. (2006) evaluated the necessity of conducting 8-hr measurement on Rn and CO_2 and proposed that intermittent measurement periods could provide the same measurement results at certain confidence level with 50% and 30% less time required, respectively. Mui, Wong et al. (2006) studied the significance of different sampling point density scenarios as compared with the Scheme and found that when the number of sampling points was reduced by 50%, the probability of getting the CO_2 level at the same confidence level would only decrease by 10%.

To minimize the efforts for measuring so many IAQ parameters, two approaches were proposed to assess IAQ: i) health-related approach; and ii) surrogate indicator approach. Health-related IAQ assessment methods target on identifying a dose-response relationship, also known as an exposure-response relationship, which describes the change in the magnitude of health effects when exposed to a stressor over a range of exposure levels and times. One example was for every 10µg/m^3 increase in PM_{10}, 0.69% increase in mortality is observed (Daniels, Dominici et al., 2000). Although a clear relationship between PM_{10} level and mortality rate was established, some other IAQ parameters do not cause observable health effects unless at extremely high concentrations.

CO_2, for example, is found to be closely associated with SBS (Seppänen, Fisk et al., 1999), yet its effects on health are subtle and non-lethal. As extensive research and testing are required, it can be extremely expensive to develop a health-related IAQ assessment tool.

Under such circumstance, surrogate indicator approach may be helpful to evaluate IAQ with less resources. Hui, Wong et al. (2006) proposed an Express Assessment Protocol (EAP) to evaluate IAQ problems in offices by identifying the main contributors to unacceptable IAQ. It was found that for Excellent Class, 96% of unacceptable IAQ could be identified by measuring TVOC, PM and HCHO; for Good Class, 93% could be screened out from the measurement of TVOC, ABC, RH, HCHO and O_3. The EAP provides an alternative for IAQ assessment by screening out the majority of premises with poor IAQ without the need to conduct a full assessment. Further to that, by investigating the probable correlations among the 12 IAQ parameters, Wong, Mui et al. (2006) proposed using CO_2, PM and TVOC, parameters that are independent to each other while having significant correlations with other parameters, as the surrogate indicators for evaluating IAQ in offices. CO_2, PM and TVOC represent occupant load and ventilation rate, system filtration performance and indoor activities, and emissions from building materials and finishes respectively, which serve as good indictors for general IAQ of an environment with ventilation system.

<u>Prediction models</u>

Based on the aforementioned efforts for simplifying IAQ assessment, an efficient and cost-effective IAQ surveillance protocol was proposed by Wong, Mui et al. (2007) for identifying asymptomatic IAQ problems. IAQ index, the average fractional dose to exposure limits of the representative pollutants, is defined in Equation 2.7.

$$\theta_q = \frac{1}{q}\sum_{\gamma=1}^{q}\phi_\gamma{}^*; \qquad \phi_\gamma{}^* = \frac{\phi_\gamma}{\phi_{\gamma,0}} \qquad \text{– (2.7)}$$

Using surrogate indicators CO_2, PM_{10} and TVOC, and Good Class exposure limits, the proposed IAQ index was used to diagnose unsatisfied IAQ in air-conditioned offices (Mui, Hui et al., 2011). IAQ indices from 525 offices were evaluated using a 5-level screening test with thresholds determined by likelihood ratios (L_r) of unsatisfactory IAQ. A $L_r > 1$ indicates a high-risk sample having an excessive occurrence of unsatisfactory IAQ, whereas a $L_r < 1$ identifies a low risk sample. The calculation steps of L_r are shown in Equations 2.8–2.9 and the levels are listed in Table 2.5.

$$L_r = \frac{P_s}{1 - P_f} \qquad \text{– (2.8)}$$

$$P_s = \frac{TP}{TP+FN}; \qquad P_f = \frac{TN}{TN+FP} \qquad \text{– (2.9)}$$

Table 2.5 Screening test of 525 air-conditioned office (Mui, Hui et al., 2011)

Test result	IAQ index	Fail IAQ		Pass IAQ		Likelihood ratio
		Counts	%	Counts	%	
Very negative	<0.32	5	3%	93	26%	0.1
Moderately negative	0.32–0.42	24	14%	131	37	0.4
Slightly negative	0.43–0.53	33	20%	85	24%	0.8
Moderately positive	0.54–0.64	33	20%	43	12%	1.7
Very positive	≥0.65	72	43%	6	1.7%	25
	Total	167	100%	358	100%	

Given the pre-test probability (P_d) of unsatisfactory IAQ and the regional failure percentage of the Scheme, post-test probability (P_d') of office with unsatisfactory IAQ can be estimated using the IAQ screening test. Equations 2.10–2.11 show the computation of pre-test probability and post-test probability of unsatisfactory IAQ.

$$P_d = \frac{n_u}{n}; \qquad O_d = \frac{P_d}{1-P_d} \qquad – (2.10)$$

$$P_d{}' = \frac{O_d{}'}{1+O_d{}'}; \qquad O_d{}' = O_d L_r \qquad – (2.11)$$

This screening test with representative IAQ parameters provides a much simpler and cost-effective alternative for IAQ assessment. If an environment "fails" in the screening test (i.e. either one of the three surrogate indictors exceeds the exposure limit), immediate remedies can be decided on to improve the IAQ. If not, based on the post-test probability given by the screening test, facility management can determine the threshold of test and threshold of remedy in regard to the willingness to invest manpower and resources on improving IAQ. Further tests, a comprehensive one, will only be needed if the screening test result is in between the two thresholds (Mui, Hui et al., 2011).

Despite the fact that economical IAQ assessment is proposed, and tremendous efforts have been put onto encouraging IAQ management, IAQ situation in Hong Kong does not seem to be improved. Existing IAQ assessment methods are not able to identify IAQ problems instantaneously. Problems are only spotted if complaints are received, or if IAQ assessment is scheduled to be conducted, which leaves occupants prone to IAQ-related sicknesses and diseases. Furthermore, premises lacking IAQ management would put users at high risk of exposure to elevated levels of IAQ pollutants without even knowing about it. A simple and economical IAQ evaluation framework for long-term IAQ monitoring is therefore required to quickly identify IAQ problems, recognize the possible sources and therefore allow the facility management/ building management system to act accordingly to mitigate the problems. Only in case the problem persists, a full IAQ assessment is needed to find out the root cause of problematic IAQ.

2.3.3. Overall IEQ

Overall IEQ discusses about the effects of a combination of various environmental aspects on occupant's satisfaction. Scope of overall IEQ can be anything that affects environmental quality, including physical environment and psychological perception. As discussed in previous sub-chapter, the intricacy and subjective nature of comfort sense has made it arduous to conduct a comprehensive assessment on IEQ that covers all IEQ influencing factors, let alone developing a mathematic model to predict IEQ acceptance that is universal for all environments. To simplify IEQ evaluation process, subjective assessments that explore occupant's comfort and satisfaction, objective assessment methods that capture the physical state of IEQ, or both, are conducted to determine the level of IEQ based on the aspects of thermal comfort, IAQ, aural and visual comfort, the major physical factors that have been found to largely influence occupant's satisfaction.

<u>Assessment methods</u>

Subjective IEQ assessment reflects actual occupant's satisfaction in form of evaluation survey. Conducting survey is simple and cost-effective as it does not require professional technique. There are many different survey tools available in literature for IEQ assessment (Peretti and Schiavon, 2011), some significant ones are exhibited in Table 2.6. All of them investigate the past IEQ experience of occupants in premises, thereby taking into the account of adaptation and subjective perception. Some further identify occupant's right-now satisfaction towards the indoor environment. One of the problems encountered for past experience assessment is to identify the most suitable time that is representative enough for surveying. It can be days, weeks, months, or even years before one's perception towards a particular environment becomes steady. Evaluating the environment based on an overall satisfaction for a period of time may create bias and as a result affecting any environmental management strategies established based on the assessment result. Alternatively, repeated right-now survey asking for the satisfaction of the environmental conditions at the exact moment of survey over the course of time can address the aforementioned problem (Heinzerling, Schiavon et al., 2013), however, too many surveys may eventually lead to survey fatigue (Porter, Whitcomb et al., 2004).

Objective measurement of physical environment is required for some subjective assessment protocols, but the determination of IEQ for these subjective assessment methods are given by considering only the occupant's opinion regardless the actual physical condition of the environment (Heinzerling, Schiavon et al., 2013). While survey captures the qualitative evaluation of an environment, without an established linkage between subjective evaluation and objective parameters, practitioners fail to improve the IEQ by adjusting the environmental parameters to standardized acceptable limits.

Table 2.6 Subjective IEQ surveys (Peretti and Schiavon, 2011)

Reference	Survey	Mode	IEQ aspects	Physical measurement	Survey structure
Womble, Girman et al. (1995)	Building Assessment Survey and Evaluation	Long-term	Physical environmental information and conditions, health and well-being, job details	CO, CO_2, VOCs, $PM_{2.5}$, PM_{10}, air temperature, relative humidity, fresh air supply	33 questions and additional comments
Nicol and McCartney (2001)	Smart Controls and Thermal Comfort	Long-term	Thermal comfort, IAQ, visual and aural comfort, productivity, general comfort	CO_2, temperature, relative humidity, air velocity, illuminance, noise level, outdoor environmental parameters	16 questions in transverse survey, 5 in longitudinal survey
Huizenga, Laeser et al. (2002)	CBE survey	Long-term & right-now	Layout and furnishings, thermal comfort, IAQ, visual and aural comfort, cleanliness and maintenance, general satisfaction	Not required	60 questions and more for custom modules
Toftum and Lantner (2005)	Remote Performance Measurement ICIEE-DTU	Long-term & right-now	Thermal comfort, IAQ, visual and aural comfort, health and productivity, personal control opportunity, general comfort and satisfaction	Not required	General perception of the environment, effects on occupants of intervention performed
Leaman (2010)	BUS occupant survey	Long-term	Thermal comfort, IAQ, perceived comfort, health, self-assess productivity, personal control	Not required	24 questions on comfort, 10 on personal control, 17 on occupant’s background, health, productivity and design
Bluyssen, Aries et al. (2011)	HOPE project	Long-term	Thermal comfort, IAQ, aural comfort, health	Chemical, biological and physical parameters	5 comfort questions, 7 SBS-related questions, 12 illness indicators

Objective assessment methods, on the other hand, quantitatively evaluate IEQ by measurement of physical parameters, which requires professionals to handle some expensive instruments, hence a much higher cost than subjective evaluations. The measurement results are compared to comfort criteria to define the category or class of the IEQ, which are established beforehand by experts, or developed by previous studies that investigate the linkage between subjective evaluations and objective parameters. Complex and time-consuming measurement process also limits the scale of assessment.

To summarize the overall IEQ performance through measurement, standardizing the measurement protocols is necessary. Table 2.7 lists out some IEQ measurement protocols available in literature. The protocols have different measurement duration requirements, ranging from minutes to up to a week. Still, it captures only a snapshot of IEQ of premises (Heinzerling, Schiavon et al., 2013). The spatial and temporal resolutions that make up a representative sample size to determine the overall IEQ depend largely on the characteristic and dynamic of the environment.

Table 2.7 Objective IEQ measurement protocols

Reference	Protocol	Location	IEQ aspects
Chiang, Chou et al. (2001)	POE	Elderly center	Thermal comfort, IAQ, lighting, and acoustics
USEPA (2003)	EPA protocol	Office	Thermal comfort, IAQ, lighting, and acoustics
Hunn, Haberl et al. (2012)	Performance Measurement Protocols	Commercial Buildings	Energy, water, thermal comfort, IAQ, lighting, and acoustics
Choi, Loftness et al. (2012)	POE	Office	Thermal comfort, IAQ, lighting, and acoustics
ISO (2012)	ISO28802:2012	All indoor environment	Thermal comfort, IAQ, lighting, and acoustics, vibration
Turunen, Leivo et al. (2016)	INSULATE project	Multi-family buildings	Thermal comfort, IAQ

Prediction models

IEQ modelling looks for the deterministic causal connections between environmental quantities and occupant's comfort. It is assumed that these relationships are purely physical which can be expressed in a mathematical equation or model (Baggs and Chemero, 2019, Willems, Saelens et al., 2020). Therefore, IEQ model attempts to correlate multiple IEQ parameters into a single index representing the overall IEQ, which is further related to occupant's subjective satisfaction. These established linkages between subjective evaluations and objective parameters are essential especially for design planning and formulating mitigation strategies, when either one of the assessment approaches is not feasible (Catalina and Iordache, 2012). Table 2.8 summarizes some subjective-objective IEQ models developed previously with weightings of individual aspects reported. Due to the interconnections and interdependency, as well as the prioritization of IEQ parameters on overall IEQ discussed in the previous sub-chapter, weightings (relative importance) of IEQ aspects determined from subjective survey vary among studies. It can be concluded that the quality of subjective satisfaction data collected from field survey greatly influences the relative weightings of each component to overall IEQ. The currently established relationships between satisfactions and environmental conditions depend on a number of features including occupants, building usage, task, etc.

Table 2.8 Selected subjective-objective IEQ models with weightings reported

Reference	Physical measurement	Subjective survey	Location	Sample size	Statistical relationship	IEQ weighting
Mui and Chan (2005)	Thermal comfort: T_a, T_{rad}, T_g IAQ: CO_2 Visual: horizontal illuminance Aural: noise level	Sensation vote and acceptability	Office	422	Linear regression for individual aspects, multivariate regression for overall IEQ	Thermal: 0.42 IAQ: 0.09 Aural: 0.28
Wong, Mui et al. (2008)	Thermal comfort: T_o IAQ: CO_2 Visual: illumination level Aural: equivalent noise level	Acceptability	Office	293	Linear regression for individual aspects, multivariate regression for overall IEQ	Thermal: 6.09 IAQ: 4.88 Aural: 4.74 Visual: 3.7
Lai, Mui et al. (2009)	Thermal comfort: T_a, T_g, RH, v_a IAQ: CO_2 Visual: horizontal illuminance Aural: sound pressure level	Evaluation scale and acceptability	Residential building	125	Linear regression for individual aspects, multivariate regression for overall IEQ	Thermal: 22.1 IAQ: 1.609 Aural: 11.77 Visual: 21.86
Cao, Ouyang et al. (2012)	Thermal comfort: PMV, PPD IAQ: CO_2 Visual: horizontal illuminance Aural: sound pressure level	Acceptability	School and office	500	Linear regression for individual aspects, multivariate regression for overall IEQ	Thermal: 0.32 IAQ: 0.118 Aural: 0.224 Visual: 0.171
Ncube and Riffat (2012)	Thermal comfort: PPD IAQ: CO_2 Visual: horizontal illuminance Aural: sound pressure level	Evaluation scale and acceptability	Office	68	Multivariate regression for overall IEQ	Thermal: 0.30 IAQ: 0.36 Aural: 0.18 Visual: 0.16

Some researchers disapprove the subjective nature of IEQ evaluation based on correlating occupant's satisfaction with field measurement data of individual aspects and overall IEQ, as subjective assessment by occupants can only reveal perceptible qualities or problems, which tends to be comfort-based and lacks health implications. Another major limitations is that subjective responses are highly influenced by environmental performance at the time of the survey, therefore the resulting weightings are building and season-specific (Rohde, Steen Larsen et al., 2020). Humphreys (2005) also stated the difficulty of using a combined index to evaluate IEQ as it depends too much on the relative importance of individual aspects which is task-specific, occupant-specific and time-dependent. While large sample size of subjective survey may be able to reduce the bias, health-related IEQ issues, especially for IAQ, are still likely to be underrepresented.

Alternatively, some support the determination of IEQ criteria and weightings through expert opinions, as building experts are equipped with experience and research knowledge to avoid personal preferences and to decide on an agreed set of weightings based on potential risks and consequences (Rohde, Steen Larsen et al., 2020). Chiang and Lai (2002) proposed a set of physical environmental indicators covering thermal comfort, IAQ, acoustic, illumination and electromagnetic field to assess the IEQ of dwellings and offices. Based on feasibility, practicability, resource consideration as well as expertise consultation, the assessment criteria and the weightings of each category to the overall IEQ were established. Larsen, Rohde et al. (2020) also developed an IEQ-Compass to evaluate residential buildings based on 16 indoor parameters from thermal comfort, IAQ, acoustic and visual aspects. The overall IEQ is assessed by a fixed set of weightings of the parameters and assessment criteria determined by building professionals and experts.

In fact, IEQ aspect of some sustainable building certification schemes adopted such approach to benchmark an environment. For example, LEED evaluates the IEQ category of building sustainability by adopting a weighting scheme for each impact category, determined by volunteer experts in green building, based on its severity, scope and scale, reversibility, contribution of built environment and solutions addressed (USGBC, 2012).

While most buildings are designed and operated according to comfort criteria recommended by building standards or certification schemes, it has been found that even if comfort requirements were met, occupants still felt unsatisfied (Burge 2004). The assessment classes of IEQ criteria also lack justifications and are not always aligned with occupant's actual satisfaction (Heinzerling, Schiavon et al., 2013). It has been acknowledged by ASHRAE (2016) that "Meeting the requirements of standards for various aspects of indoor environments, such as air quality, thermal conditions, acoustics, or illumination, is not always sufficient to ensure the acceptability of the environment to all relevant parties."

In spite of the robustness of detailed assessment criteria and strong professional and academic backup for the determination of assessment basis, these weighting tools evaluate, from an expert point of view, the building's potential to provide a comfortable and healthy indoor environment, without reflecting the actual environmental conditions perceived by occupants. Both occupant influences on the indoor environment as well as their personal preference and adaption, which have substantial impacts on perceived IEQ, are not considered in these assessment methods (Larsen, Rohde et al., 2020). In addition, these weightings treat individual aspect separately, despite research has indicated, as discussed in previous sub-chapter, interaction between aspects exist in which occupants would balance the good one with the bad one to reach overall satisfaction (Humphreys, 2005). Interconnections and interdependency of IEQ aspects have not been considered in any existing objective-criteria model.

Subjective-objective approach correlates environmental parameters with occupant's subjective satisfaction, which can genuinely reflect the perceived IEQ as well as establish the relationship between environmental parameters and satisfaction, but lacks energy, health implications and objectivity (Heinzerling, Schiavon et al., 2013, Rohde, Steen Larsen et al., 2020). On the other hand, objective-criteria approach using expert's opinion models the overall IEQ by objectively relating environmental parameters with building IEQ performance, which appears to be impartial, standardized and professional to assess the IEQ capability, but neglects the influence of one of the most important IEQ factors – the occupants. As much as the building fulfils comfort criteria, it does not necessarily satisfy the building occupants.

Heinzerling, Schiavon et al. (2013) emphasized in their review that as much as a combined overall IEQ index based on weightings of individual aspects can be beneficial for benchmarking and rating an environment, a loss of information may be resulted as the model fails to universally address all environment aspects for all indoor environments. Willems, Saelens et al. (2020) also agreed that considering occupant's perception towards an environment as a causal, reducible relationship (i.e. a mathematical model) may be easier for setting up building guidelines and comfort requirements, but it may not be able to truly reflect the actual experience when it comes to different occupants. There is an undeniable fact supported by literature that relative weightings of IEQ aspects on overall IEQ depend on so many factors, including physical, functional (task-related) and psychological (occupant-related) factors, and these linkages between subjective evaluations and objective parameters are likely to change with time and lived experience. It is apparent that the causal relationship sometimes cannot explain people's conscious experience to environmental conditions that is ever-changing (Stanton, 1983). IEQ modelling therefore cannot fully adopt a reductive physicalism in exploring the relationship between environmental quantities and occupant's satisfaction. Even though phenomenal characteristics of mental state, perception, feelings and emotions can be revealed through surveys and questionnaires with occupants, we cannot solely rely on field questionnaires to evaluate building IEQ performance due to its subjective nature and the lack of universal judgement (Asadi, Mahyuddin et al., 2017). For that reason, the best approach is to incorporate certain extent of subjective assessments such that the unique relationship between environmental parameters and occupant satisfaction are conveyed in IEQ model.

2.4. Summary

IEQ is of great importance to building owners, businesses and occupants due to its effects on health, comfort and productivity. Comprehensive assessment methods for IEQ aspects and overall IEQ are therefore crucial for building designers, engineers and operators to evaluate building performance based on health risks, occupant's satisfaction and comfort levels. This chapter reviews the impacts of IEQ, related influencing factors and methods and models for evaluating IEQ of premises.

This review begins by introducing the impacts of IEQ on health and productivity. Health effects by poor IEQ include short-term SBS, long-term BRI and a number of acute health consequences caused by poor IAQ. Substandard IEQ can lead to absenteeism and presenteeism, as a result lowering productivity and increasing production cost. To maintain a healthy, comfort and productive environment, IEQ assessment is essential to identify underlying environment problems and subsequently formulate mitigation measures to improve the building performance.

IEQ influencing factors, especially focusing on thermal comfort, IAQ, visual and aural comfort, are also examined and presented in this chapter. Thermal comfort, being the most discussed domain of IEQ, explores the environmental and occupant's factors that influence the thermal experience, which is found to be seasonal, occupant- and space-specific. It is often evaluated with respect to thermal sensation, neutrality and acceptability. IAQ, as the culprit of most acute health consequences, is another aspect of IEQ that must pay attention on. Three IAQ parameters, namely CO_2, PM and VOCs, have been identified to be representative as indicators for building performance, representing the occupant load and ventilation efficiency, filtration performance of ventilation system and emission from building materials, ventilation efficiency and high polluting activities respectively. Visual comfort, defined as a subjective condition of visual well-being induced by the visual environment, is found to be influenced by a number of physical and subjective factors. It is also occupant-, space- and task-specific, and highly subjective depending on one's preference and psychological state. To simplify assessment procedure, visual performance of an environment is usually objectively assessed by illuminance level. Aural comfort describes the quality of acoustic environment that protects occupants from noise and disturbance, which greatly jeopardizes productivity and work performance. As an acceptable acoustic environment is mainly task-based, amount of noise is maintained at an acceptable level suggested by building regulations and occupational standards.

Interconnections and interdependency between IEQ influencing factors are examined. These combined effects by two or more factors can be from actual physical influences of different aspects on each other, or from the alteration of occupant's psychological perception on environmental conditions with the given stimulations. A lot of research has recognized these complex interactions between various environmental parameters, classifying them as first-order interaction – interactions among factors of same environmental aspect, and second-order interaction – interactions between different environmental aspects. In addition, a prioritization of factors on overall IEQ has been observed to be occupant-, space- and task-specific, with certain degree of inconsistency. While it is important to model overall IEQ satisfaction with individual factors for the purpose understanding and improving the IEQ, it is nevertheless challenging due to the fact that individual impacts are not systematic.

The remaining part of this chapter is devoted to discuss the assessment methods and models for thermal comfort, IAQ and overall IEQ. Subjective and objective assessment methods are introduced. Subjective assessments involve asking the feelings, comfort and satisfaction of building occupants, which are the prime interests of building operators. Objective assessment methods, for example comparing field measurement data of physical environmental conditions to comfort criteria, can objectively evaluate the IEQ of an environmental without the concern of occupant’s state of mind. Both approaches have their advantages and drawbacks. Subjective survey is able to capture the qualitative evaluation of an environment, while objective measurement can quantitatively evaluate IEQ by measurement of physical parameters. Nevertheless, without an established linkage between satisfaction and environmental condition, practitioners fail to improve the IEQ by adjusting the environmental parameters to standardized acceptable limits. IEQ modelling is therefore the key to the ultimate goal of improving IEQ.

IEQ modelling attempts to understand the deterministic causal relationships between environmental parameters and occupant’s comfort by expressing these relationships using a mathematical equation or model. Multiple IEQ parameters are combined into a single index representing the overall IEQ, which is further correlated to occupant’s subjective satisfaction. Review of existing studies found diverse range of weightings, suggesting that the quality of subjective satisfaction data greatly influences the relative weightings of each component to overall IEQ. Also, subjective assessment by occupants can only reveal perceptible IEQ problems, which tends to be comfort-based and lacks health implications. Alternatively, some determine the weightings by expert's opinions, which can avoid personal bias and provide professional judgement on weightings that are based on potential risks and consequences. However, these weightings fail to reflect the actual environmental conditions perceived by occupants, and occupant's influences on IEQ satisfaction is not considered.

Either way, none of these weightings, when used alone, can genuinely reflect the IEQ satisfaction of occupants. These linkages have been proven to depend on many factors including physical, functional and psychological elements, and are likely to change with time and lived experience. While surveys and questionnaires can reveal the mental state, perception, feelings and emotions of occupants, objective basis is required to ensure fair judgement and universality. On this account, there is a need to have an accurate and updated comfort model that incorporates the significance of field data to improve IEQ satisfaction prediction, wherefore assessing an indoor environment based on the distinctive thoughts and perceptions of the building occupants.

Chapter 3. Performance of thermal comfort models

3.1. Introduction

A lot of IEQ research focuses on thermal comfort rather than the other three aspects. It is probably because of the huge energy consumption of the system in providing a comfortable thermal environment. Thermal comfort models adopt a subjective-objective approach to relate physical thermal loads with thermal sensations and satisfaction acquired in controlled experiment or in field. One of the most popular ones is Fanger's PMV/PPD model. Many existing building design guidelines and building standards use PMV/PPD model as the basis of assessment criteria. However, discrepancies between model predictions and actual thermal sensations and satisfaction from field survey have been observed in many studies covering various kinds of indoor environments.

To recognize and understand such inadequacy, a thorough literature search is conducted to gather thermal comfort field response data available in open literature. These data are compared to predictions by PMV/PPD model to identify the disparities. Application of PMV/PPD model for energy saving potential is presented, and the resulting disagreement estimated by field responses and prediction model are determined.

In additional to evaluating thermal comfort model in awakening state, which has been extensively researched on, sleeping thermal environment, thermal sensation, satisfaction and sleep quality in dormitory are also studied. Given that sleep quality is largely affected by physiological, psychological and external stimulations, based on physical measurements and comfort questionnaires, associations between sleeping thermal environment and subjective comfort are identified. The main aim is to identify the effect of contextual factors on thermal comfort sensations which is not considered and factored into conventional thermal comfort models based on heat balance of human body, and to demonstrate the importance of having different thermal comfort requirements for different kind of daily activities, therefore having thermal comfort models that are appropriate to various settings and types of occupants.

By studying the existing thermal comfort models, this chapter presents the negative impacts of using an inaccurate prediction model in research and practical application, demonstrating the importance of having accurate and updated comfort prediction models.

3.2. Thermal comfort field data and predictions by model

A comprehensive literature search is carried out to search for and collect openly available thermal comfort field data. Discrepancies between actual and predicted results of thermal sensations (TSV and PMV) and thermal satisfactions (actual percentage dissatisfied (APD) and PPD) of occupants can be found in literature. The correlation between TSV and PMV can be expressed by Equation 3.1.

$$TSV = C_1 \times PMV + C_0 \qquad \text{– (3.1)}$$

Research has shown that this correlation depends on the following: ventilation system type, thermal perception, tolerance and adaptation of occupants, occupant characteristics (gender and age), climatic or seasonal variation, and the state of environmental characteristics (i.e. steady or transient) (Cardoso, Ramos et al., 2018, Lu, Pang et al., 2018, Rupp, de Dear et al., 2018). Table 3.1 summarizes some on-site thermal comfort assessment results from 2014 to 2018. C_1 and C_0 shown were either acquired from the data reported in the study, or estimated from graph provided. The differences found between TSV and PMV suggest that PMV model adjustment is required for actual field use.

Table 3.1 Occupant's TSV in various studies from 2014 to 2018 (continued on next page)

Reference	Location	Building	Ventilation	Köppen–Geiger climate	Season	Sample size	C_1	C_0	TSV (no. of vote)						
									-3	-2	-1	0	1	2	3
Lu, Pang et al. (2018)	Hainan, China	Residential building	FR	Dry-winter humid subtropical	Transitional season	1944	0.94	-0.31	–	–	–	–	–	–	–
Cheng, Fu et al. (2018)	Tibet, China	Stone dwellings	NV	Cold semi-arid	Winter	327	1.37	0.98	27	41	154	95	11	0	0
Yu, Li et al. (2017)	Tibet, China	Residential building	NV	Cold semi-arid	Summer	609	0.69	0.38	8	26	129	351	74	17	4
					Winter	573	0.76	0.39	13	18	51	202	173	79	37
Ning, Wang et al. (2016)	Harbin, China	Residential building	H	Monsoon-influenced hot-summer humid continental	Cool exposure	304	1.13	0.76	4	6	62	187	24	19	2
					Warm exposure	321	0.73	0.02	0	2	28	209	40	20	22
Yang, Nam et al. (2016)	Korea	Elderly centre	NV/AC/H	Hot-summer humid continental	Cooling	114	0.32	0.15	0	0	4	68	40	2	0
					Mid-season	182	1.16	0.44	8	22	50	80	22	0	0
					Heating	102	0.84	0.15	2	26	42	20	10	2	0
Jiao, Yu et al. (2017)	Shanghai, China	Elderly home	FR	Humid subtropical	Winter	342	0.60	0.39	1	52	33	212	43	1	0
					Summer	330	0.37	0.04	0	0	11	188	82	46	3
Rupp and Ghisi (2017)	Brazil	Office building	AC	Tropical savanna/ Humid subtropical	Spring to early winter	1236 (A)	0.51	0.15	5	48	328	713	132	10	0
			AC/NV			823 (B)	0.49	0.22	3	24	180	461	139	13	3
			AC/NV			530 (C)	1.08	0.66	0	6	115	266	106	27	10
Thapa, Bansal et al. (2018)	India	Office	AC	Hot semi-arid/ Tropical savanna	All year	444	0.96	0.27	1	33	166	165	71	8	0
Kajtar, Nyers et al. (2017)	Hungary	Office	AC	Warm humid continental	Winter	278	1	0.28	NA	50	106	72	31	19	NA
Gallardo, Palme et al. (2016)	Quito, Ecuador	NV office	NV	Temperate oceanic	Summer	441	0.32	0.07	7	12	88	246	81	7	0
Manu, Shukla et al. (2016)	India	Office	NV	Hot semi-arid/ Tropical savanna	All year	2005	0.8	0.66	–	–	–	–	–	–	–
			NV/AC			2470	0.76	-0.49	–	–	–	–	–	–	–
			AC			1849	0.65	-0.53	–	–	–	–	–	–	–

Table 3.1 Occupant's TSV in various studies from 2014 to 2018 (continued on next page)

Reference	Location	Building	Ventilation	Köppen–Geiger climate	Season	Sample size	C_1	C_0	TSV (no. of vote)						
									-3	-2	-1	0	1	2	3
Luo, Cao et al. (2015)	Shenzhen, China	Office	AC	Monsoon-influenced humid subtropical	Summer	321	0.57	0.14	3	9	16	174	102	11	6
			NV			513	0.46	0.06	21	45	17	241	183	4	2
Hamzah, Gou et al. (2018)	Makassar, Indonesia	Secondary school	NV	Tropical monsoon	Summer	1594	0.68	-1.05	0	21	317	588	493	167	8
Fang, Zhang et al. (2018)	Hong Kong, China	University classroom (Chamber)	HVAC	Monsoon-influenced humid subtropical	Summer	946	0.67	0.38	–	–	–	–	–	–	–
Liu, Jiang et al. (2017)	Weinan and Wuwei, China	Rural school	NV	Cold semi-arid	Winter	763	0.42	-0.10	11	58	230	362	82	17	3
Wang, Jiang et al. (2017)	Shaanxi, China	School	H/NH	Cold semi-arid	All year	345	0.45	0.1175	14	45	110	131	36	8	1
	Gansu, China			Cold semi-arid		360	0.35	0.13	6	16	70	213	40	11	4
	Qinghai, China			Cold semi-arid		421	0.39	-0.51	3	14	68	126	126	69	15
Calis and Kuru (2017)	Aegean, Greek	Classroom	HVAC	Hot-summer Mediterranean	Heating	449	0.97	0.29	0	14	36	139	139	85	36
					Cooling	345	1.29	0.03	14	24	42	62	69	55	79
Hamzah, Ishak et al. (2016)	Indonesia	University classroom	NV	Tropical rainforest	Autumn	118	0.46	0.43	0	0	19	26	50	20	3
Cardoso, Ramos et al. (2018)	Porto, Portugal	Bus station	MVS	Warm-summer Mediterranean	Summer	240	0.60	1.07	0	1	17	105	71	38	8
Wang, Sun et al. (2018)	Shandong, China	Rubber factory	NV	Hot humid continental	Summer	40	0.89	-1.21	0	0	2	10	16	10	2

Table 3.1 Occupant's TSV in various studies from 2014 to 2018

Reference	Location	Building	Ventilation	Köppen–Geiger climate	Season	Sample size	C_1	C_0	TSV (no. of vote)						
									-3	-2	-1	0	1	2	3
Sattayakorn, Ichinose et al. (2017)	Bangkok, Thailand	Hospital	AC	Tropical savanna	Summer	451 (Patient)	0.52	0.004	5	45	74	255	41	25	6
						146 (Staff)	1.24	-0.98	8	27	45	25	20	14	7
						331 (Visitor)	0.63	0.05	8	36	61	182	26	18	0
Liu, Lian et al. (2018)	China subtropical monsoon area	Ship cabin	AC	Monsoon-influenced humid subtropical	Winter	100 (Seated)	0.97	0.44	–	–	–	–	–	–	–
						100 (Light working)	1.24	1.13	–	–	–	–	–	–	–
Yang, Liu et al. (2015)	Henan, China	Cotton textile workshop	AC	Humid subtropical	Summer	123 (Worker)	0.59	0.34	0	0	0	6	42	48	27
						69 (Student)	0.91	0.76	0	0	0	0	16	29	24
Yang, Li et al. (2015)	Chongqing, China	Environ-mental chamber	Controlled	Humid subtropical climate	All year	440	0.45	-0.1	–	–	–	–	–	–	–
Hussin, Salleh et al. (2015)	Penang, Malaysia	Mosque	AC	Tropical rainforest	Cooler and hotter seasons	330	0.25	-0.39	1	5	39	108	105	69	3

MVS–mechanical ventilation system; AC–air-conditioned; FR–Free-running; HVAC–Heating, ventilation, and air conditioning; NV–natural ventilation; H/NH–Heating/ no heating.

Remark: '–' indicates that the TSV values are not available in the corresponding studies; *a 5-point scale was used for thermal sensation evaluation.

As buildings are designed to provide an acceptable environment for the occupants, extreme TSV values (i.e. +/ -3, representing hot and cold) are rarely seen in field settings. According to Table 3.1, +/ -3 votes contributed an average of 5.08% to the total number of thermal votes. Depending on the analysis method adopted, such a small sample size (e.g. less than 5 extreme votes in some assessments) will make the regression output either statistically insensitive or biased. As a result, the reliability of the extrapolated PMV–TSV regression is questionable (Wong, Mui et al., 2014).

Similarly, the thermal acceptance of occupants was found different when compared to Fanger's PPD model. Some field study results from 2014 to 2018 are summarized in Table 3.2 for the purpose of comparing the predicted and the actual dissatisfaction under various thermal sensation votes. A field study conducted in a tropical island region–Hainan, China, reported that the APD at an extreme value of TSV (-3: 8.7% or +3: 40.91%) was much lower than the corresponding PPD (99%). In that study, there were 59.7% and 43.5% of occupants expecting no changes in indoor temperature at TSV = -2: cool and TSV = -3: cold respectively (Lu, Pang et al., 2018). Another study carried out in Bangkok hospitals showed that while the medical staff were satisfied with thermal neutrality, patients and visitors preferred a warmer environment (Sattayakorn, Ichinose et al., 2017). In fact, many studies of thermal preferences revealed a broader thermal acceptance range among building occupants (Rupp and Ghisi, 2017, Sattayakorn, Ichinose et al., 2017, Hamzah, Gou et al., 2018, Kim and de Dear, 2018, Liu, Lian et al., 2018), which can be due to thermal tolerance and adaption (Mui, Tsang et al., 2019, Ghaffari Jabbari, Maleki et al., 2020). These findings suggested a certain degree of disagreement between field outcomes and PPD by Fanger's model.

Table 3.2 Review of actual percentage dissatisfied (APD; %) in various studies from 2014 to 2018

Reference	Location	Building	Types of ventilation	Köppen–Geiger climate	Season	Total sample size, $\sum n$		TSV -3	TSV -2	TSV -1	TSV 0	TSV 1	TSV 2	TSV 3
Lu, Pang et al. (2018)	Hainan, China	Residential building	FR	Dry-winter humid subtropical	Transitional season	1944	APD (%)	8.7	2.3	2.8	2.8	19.3	23.2	40.9
Sattayakorn, Ichinose et al. (2017)	Bangkok, Thailand	Hospital	AC	Tropical savanna	Summer	451 (Patient)	APD (%)	66.2	31.5	8.5	0	3.1	9.2	22.3
						146 (Staff)	APD (%)	91.5	62.3	26.2	7.7	11.5	23.1	38.5
						331 (Visitor)	APD (%)	71.5	34.6	8.5	0	2.3	6.2	16.2
Kim and de Dear (2018)	New South Wales, Australia	Primary school	NV/AC	Humid subtropical climate	Summer	3545	APD (%)	85	49	16	8	17	38	65
		Secondary school				1321	APD (%)	60	23	8	9	20	43	72
Dias Pereira, Raimondo et al. (2014)	Beja, Portugal	Classroom A	HVAC	Hot-summer Mediterranean	Spring to summer	26	APD (%)	NA	NA	17	0	0	NA	NA
		Classroom B				19	APD (%)	NA	NA	NA	1	0	0	NA
Jiao, Yu et al. (2017)	Shanghai, China	Elderly home	FR	Humid subtropical	Winter	342	APD (%)	100	94	79	0	7	100	NA
					Summer	330	APD (%)	NA	NA	27	0	84	87	100
							Min	8.7	2.3	2.8	0	0	0	16.2
							Max	100	94	79	9	84	100	100
							Mean	69.0	42.4	21.4	2.9	16.4	36.6	50.7
								PMV -3	PMV -2	PMV -1	PMV 0	PMV 1	PMV 2	PMV 3
Predicted percentage dissatisfied % (PPD) in Fanger's model								99	75	25	5	25	75	99

FR–Free-running; NV–natural ventilation; AC–air-conditioned; HVAC–Heating, ventilation, and air conditioning.

Remark: 'NA' due to 0 sample size under the vote.

While thermal sensation is related to thermal environmental parameters, thermal acceptance examines whether the thermal environment is acceptable to building occupants. From a practical point of view, discussing the sensation may not be useful if the correlation between sensation and acceptance is inconsistent most of the time. According to the field study results, a -3: cold, -2: cool, +2: warm or +3: hot sensation does not necessarily mean unacceptable thermal environments, and a 0: neutral sensation does not imply an acceptable thermal environment.

3.3. Effects and implications of performance gap in prediction models

The development of thermal comfort models has not made much progress due to the complex relationships between physical parameters and choice-making aspects. Although Fanger tried hard to make his model as objective as possible, subjective psychological effects have increasingly been proven to exert great influences on thermal sensations and acceptance. The discrepancies between predicted and measured results suggest a performance gap in the PMV/PPD model, and that may induce research errors.

A number of studies applied PMV control to improve energy performance together with thermal comfort. For instance, a study using PMV as the reference parameter for controlling ground-source heat pump system (GSHP) to maintain thermal comfort showed that a 20% of energy could be saved without jeopardizing thermal comfort (Fang, Feng et al., 2018). Another study employing PMV control rather than dry-bulb air temperature control reported 7.3% less annual energy consumed by gas boilers and 28.8% less annual electricity used for cooling (Hong, Lee et al., 2018). Yet, regardless of how impressive these findings appear to be, their implications would not be valid or useful if the model basis itself is inaccurate.

According to the field survey, PMV = 0 does not necessarily give TSV = 0. In Table 3.1, the corresponding range of PMV to TSV = -1, 0 and +1 by Equation 3.1, and the corresponding PPD are illustrated in Table 3.3. It can be seen that TSV of -1 to +1 give a range of PMV from -3.59 to +5.64 (mean: -1.79 to +1.51), which basically cover the whole range of PPD (mean: 66.7% to 51.7%). If PMV is assumed to be equal to TSV, i.e.

as presumed in most thermal comfort studies, the PPD values for the votes TSV = -1, 0 and +1 shall be 26.1%, 5% and 26.1% respectively, indicating a PPD difference up to 73.9%.

Table 3.3 Corresponding PMV and PPD for TSV = -1, 0 and 1

TSV	Transforming TSV to PMV by Equation 3.1	PPD (Assume TSV = PMV)	PPD (Transforming TSV to PMV by Equation 3.1)
-1	-3.59–0.24 (Mean = -1.79)	26.1%	100%–6.2% (Mean = 66.7%)
0	-1.77–1.58 (Mean = -0.14)	5%	65.3%–55.2% (Mean = 5.4%)
1	-0.11 5.64 (Mean = 1.51)	26.1%	5.2%–100% (Mean = 51.7%)

The use of Fanger's model as the basis of thermal comfort research also results in differences between PPD and APD. Currently, maintaining a minimum value of 5% thermally dissatisfied persons for PMV = 0 is adopted in thermal comfort management practices and research related to system control and simulation. However, the field study outcomes in Table 3.2 revealed that occupants were actually satisfied with a wider PMV range when PMV = TSV. Examples include a study by Lu, Pang et al. (2018) that demonstrated a TSV range from -2 to 0 corresponded to ADP < 2.8%, and an assessment by Dias Pereira, Raimondo et al. (2014) that reported a minimum percentage dissatisfied when TSV ≠ 0.

If the discrepancies between PMV and TSV as well as those between PMV and PPD are taken into consideration, the PMV/PPD model may be unfit for thermal comfort analysis. This can be shown using the GSHP study by Fang, Feng et al. (2018) as an example. In that study, a non-linear relationship between PMV = -0.05–0.4 and power consumption = 1.4–2.5 kW (power consumption = 1.77 kW at PMV = 0) was described. The study also reported that a 20% of energy could be saved by maintaining the PMV at a level of -0.07, corresponding to a PPD of 5.1%. According to Table 3.4, which presents the corresponding TSV values at PMV = 0 and -0.07 determined from the assessment results in Table 3.1, however, thermal comfort (PPD < 5%) can neither be maintained at PMV = 0 nor -0.07. On the other hand, thermal comfort can be achieved at PMV = -0.14 (corresponding to a mean value of TSV = 0), while energy reduction can be attained at PMV = -0.24 (corresponding to a mean value of TSV = -0.07). The difference between PMV and TSV can be easily noticed.

Table 3.4 Corresponding TSV and PPD for PMV = 0 and -0.07

	Minimum		Maximum		Mean	
PMV = 0	TSV	-1.21	TSV	1.13	TSV	0.14
	PPD	35.7	PPD	32.0	PPD	5.4
PMV = -0.07	TSV	-1.27	TSV	1.05	TSV	0.086
	PPD	38.8	PPD	28.1	PPD	5.2

Figure 3.1 shows the power consumption for the PMV data extracted from the GSHP study, with the assumption of PMV = TSV. It should be noted that a linear relationship was assumed to simplify the calculation. Based on the field data collected from the literature search, the actual PMV values, which are calculated using Equation 3.1 and mean C_1 and C_0 from all studies (shown in Table 3.1), are plotted in the figure for comparison. The uncertainty range resulted from the difference between PMV and TSV was from 31.5% to 3.0%, with an average of 14.8%. This range is extremely significant when compared to the 20% energy savings claimed in the study.

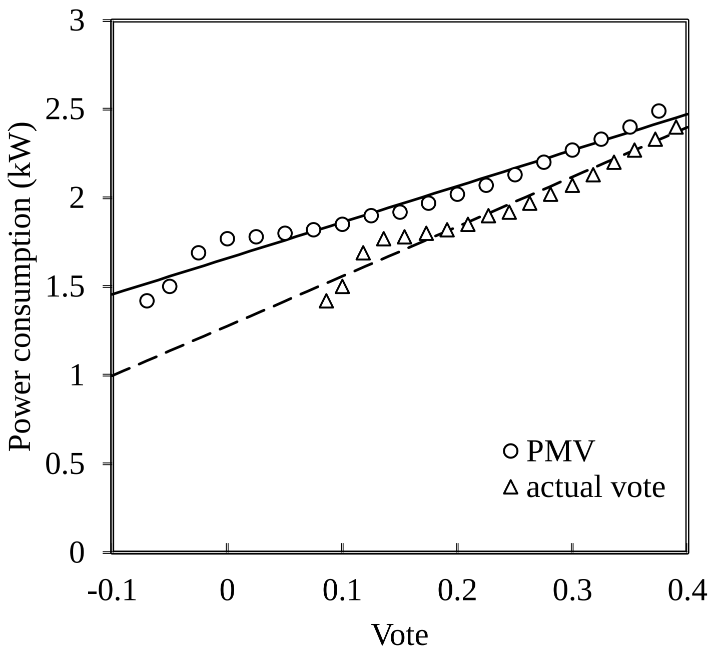


Figure 3.1 TSV against power consumption (Fang, Feng et al., 2018), actual votes were calculated using coefficients gathered from field studies

Another uncertainty can be found in the range of PMV/TSV that represents the 5% dissatisfied. Figure 3.2 exhibits the relationship between PMV and thermal dissatisfaction. It can be seen that the APD is generally lower than the PPD, resulting in a wider PMV range (i.e. PMV = -0.64–0.58) for maintaining thermal comfort level with less than 5% dissatisfied while achieving higher energy efficiency. Since the GSHP study did not discuss about the power consumption below PMV = -0.07, the effect of energy savings with a wider range of acceptable PMV values cannot be quantified when no actual energy data is available. Nevertheless, a wider acceptable PMV range offers greater energy savings potential for both heating and cooling systems.

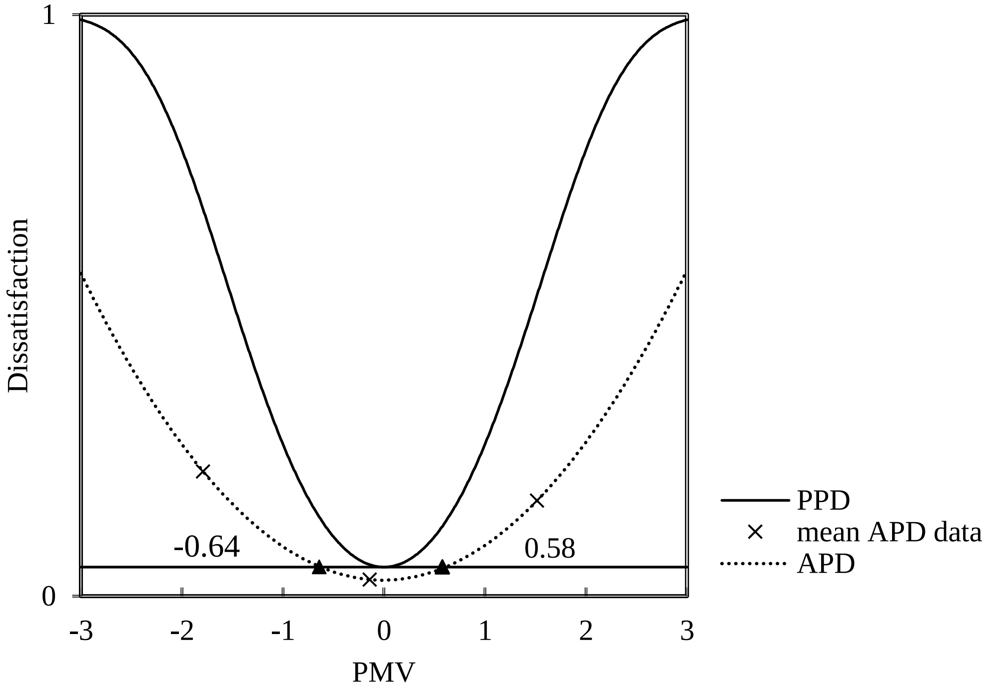


Figure 3.2 PMV against thermal dissatisfaction

3.4. Overview of sleeping thermal environment

Human spend about one-third of time sleeping, which allows recovery of body through various processes including replenishment of cerebral glycogen storage, cellular maintenance, etc. (Vyazovskiy and Delogu, 2014). It also helps remove the neurotoxins accumulated in the central nervous system during awake period (Xie, Kang et al., 2013). Sleep disruption can result in short-term health problems like headache, pain, depression and anxiety (Tkachenko, Olson et al., 2014). Poor sleep quality also impairs cognitive ability and performance (McCoy and Strecker, 2011). In long-term, sleep deprivation increases health risks like cardiovascular diseases (Narang, Manlhiot et al., 2012). Therefore, maintaining good sleep quality is important in enhancing productivity and health. Given that sleeping thermal environment has great effects on occupant's sleep quality, evaluation of sleeping thermal environment is valuable to our understanding of IEQ in living environment.

Relationship between thermoregulation and sleep has been identified, which is mainly facilitated by circadian rhythm of core temperature. Murphy and Campbell (1997) found that rapid decline in body core temperature enhanced sleep initiation and facilitated the entering of deeper stages of sleep. Kräuchi, Cajochen et al. (1999) further confirmed the contribution of thermoregulation on sleep onset, concluded from the observation of a functional linkage between vasodilation of distal skin regions and subsequent skin temperature increase at the extremities and the ability to fall asleep.

Thermal environment, besides influencing the transition from wakefulness to early stage of non-rapid eye movement (NREM) sleep, it often affects the quality of sleep. Experimental study conducted in sleep laboratory found decreases in slow wave sleep (SWS) and rapid eye movement (REM) sleep and increase in wakefulness under humid heat exposure at 35°C and 75% humidity (Okamoto-Mizuno, Mizuno et al., 1999). Hot and humid environment in summer also impaired sleep efficiency by increasing the duration of mid-night awakenings (Tsuzuki, Mori et al., 2015). On the other hand, Okamoto-Mizuno, Tsuzuki et al. (2009) suggested that cold exposure could affect cardiac autonomic responses by altering heart rate variability in stage 2 sleep and SWS, but would not affect sleep stage and subjective sensations, making an individual prone to adverse cardiac events during transition of sleep stage in winter (Viola, Simon et al., 2002). It can be concluded that maintaining a comfortable thermal environment is crucial to good sleep quality and even health. Nonetheless, most of the thermal environmental guidelines or standards were formulated to satisfy awaken people instead of sleeping people, despite that studies have shown significant difference between thermal requirements of sleeping people and their awaken counterparts (Lan, Tsuzuki et al., 2017, Song, Liu et al., 2020).

Thermal comfort studies in sleeping environment are limited, and those related to actual field data collection are lacking. The majority of sleeping thermal comfort studies investigated thermal comfort of sleeping people under controlled thermal conditions to determine the effect a particular factor on thermal comfort and/or sleep quality. For example, Pan, Lian et al. (2012) simulated winter environments (17°C, 20°C and 23°C) and investigated the sleep quality of 8 young adults based on subjective and physiological measurements. The study found that under thermal resistance of 3.12 clo, 23°C was the most satisfactory for sleeping. The sleep onset latency was also the shortest and the SWS was the longest at this temperature. Lan, Pan et al. (2014) studied the effects of 3 pre-set air temperature (23°C, 26°C and 30°C) on sleep quality and thermal comfort of sleeping people and found that sleep quality was sensitive to change in air temperature. Under clothing resistance of 1.64 clo, T_n at sleep (slightly above 26°C) was higher than that in awakening state (23°C), suggesting a difference in thermal sensation during sleep and wakefulness. On the contrary, a recent field study found that people had a lower T_n during sleep than when awake (Zhang, Cao et al., 2018). While these studies collected subjective sleep quality data, the data were only evaluated together with indoor temperature instead of the thermal sensations and satisfaction.

To identify the thermal neutral environmental conditions for sleeping people, Lin and Deng (2008) developed a theoretical thermal comfort model for sleeping environment based on energy balance of human body and Fanger's PMV model (Fanger, 1970). By introducing assumptions and modifications necessary for a sleeping person, for example metabolic rate, total thermal resistance by bedding system, etc., comfort equation for sleeping environment, hereby annotated as PMV_{sleep}, was derived, and comfort charts for sleeping environment were established by solving the comfort equation. The model suggests that total thermal insulation of bedding system significantly influences T_n, with a linear relationship with slope of -0.189 clo/°C at 50% relative humidity. Lan, Zhai et al. (2018) later developed a two-part model, labelled as $PMV_{2\text{-}part}$, for evaluating thermal neutrality for sleeping people by considering the thermal balance of body parts in contact with the bed and not separately. The model's ability to predict T_n was validated using experiment results found in literature. Comparing to predictions made by PMV_{sleep},

$PMV_{2\text{-}part}$ gave estimations that agreed better with the experimental results with less than 5% deviations.

Sleep quality is affected by physiological, psychological and external stimulations (Chen, Guo et al., 2013). Subjective thermal comfort survey is therefore more realistic and reliable in evaluating sleeping thermal environment than objective polysomnography assessment by also considers the physiological adaptability and psychological satisfaction of the subjects (Wang, Liu et al., 2015). In order to find out the linkage between subjective thermal sensations, thermal satisfaction and sleep quality, and to evaluate the ability of the two above-mentioned models to accurately predict the thermal sensation and thermal neutrality of sleeping people, actual sleeping thermal comfort field data were collected from university students residing in dormitory in Hong Kong. Thermal environmental parameters and subjective thermal sensations, satisfaction and sleep quality data were gathered and evaluated. The associations between thermal sensation, thermal satisfaction and sleep quality were also analyzed.

3.5. Field measurement of sleeping thermal condition in dorm

Field measurements were conducted in a university dormitory in Hong Kong during winter time from November 2018 to March 2019. To assess the thermal environment, indoor environmental parameters including T_a, T_g, RH, v_a were measured by Lutron Heat Index WBGT Meter (WBGT-2010SD) and TSI Air Velocity Transducer (TSI-8475) throughout the night with a logging interval of 1 min, started from before the subject sleep and ended after they woke up. Devices were placed near the head area of the subject. In thermal comfort study, convective and radiative heat loss from skin shall be expressed in terms of T_o and T_{rad}, which can be computed with Equations 3.2–3.4 below, where ε and d are the emissivity and diameter of the globe, h_c is the convective heat transfer coefficient.

$$T_{rad} = \left[(T_g + 273)^4 + \frac{1.1 \times 10^8 \cdot v_a^{0.6}}{\varepsilon \cdot d^{0.4}} (T_g - T_a) \right]^{0.25} - 273 \qquad - (3.2)$$

$$T_o = \frac{4.7 T_{rad} + h_c T_a}{4.7 + h_c} \qquad - (3.3)$$

$$h_c = \begin{cases} 5.1, & 0 < v_a \leq 0.15 \\ 2.7 + 8.7 {v_a}^{0.67}, & 0.15 < v_a < 1.5 \end{cases} \qquad - (3.4)$$

In addition to collecting thermal environmental data, interviewees were required to report their time of sleep and awakening. With reference to thermal insulation by bedding systems commonly used in Hong Kong (Lin and Deng, 2008), students were asked to select the combinations of bedding cover (i.e. blanket or quilt of various thicknesses) and sleepwear (i.e. naked, half or full-slip) they adopted during sleep and the percentage coverage of body surface area by bedding and bed (A). Since the dorm provided the same type of conventional mattress for everyone, the total clothing insulation values (I_{cl}) provided by bedding system and clothing can be estimated according to Lin and Deng (2008), and the total thermal resistance can be determined by Equation 3.5, where K is a unit constant of 6.45 clo W/m^2°C.

$$I_{cl} = KR_t \qquad -(3.5)$$

It is noteworthy that as though other environmental factors have been found to influence sleep quality, for example noise (Libert, Bach et al., 1991), the purpose here is to investigate the effect of thermal conditions on sleep quality, therefore other factors are not considered. The prime interest is to evaluate the sleeping thermal environments, and the relationship between sleeping thermal sensation, thermal satisfaction and sleep quality. Students were free to select their most comfortable environmental conditions to conduct questionnaire.

10 university students (6 males; 4 females; 18–25 years old) residing in double rooms and triple rooms of 9-person suites, shown in Figure 3.3, were interviewed. Comparable number of subjects were considered in most of the sleeping thermal comfort studies established previously. A repeated measurement design was adopted to allow fewer subjects for more efficient data collection with less variance. Students were asked to take part in the field measurement for more than 2 times, depending on their availabilities. All of them were non-smoker and non-alcoholic, and were free of chronic diseases, diagnosed sleeping disorders and any long-term medication. They were required to avoid intense

physical activities like exercising, consumption of alcohol and caffeine at least 8 hours prior to the test period to minimize the influence of daytime activities on sleep quality.

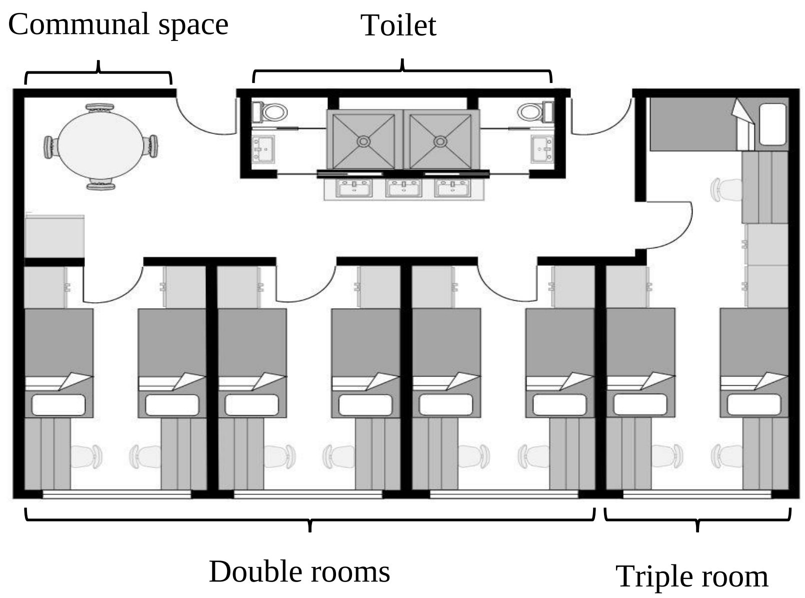


Figure 3.3 Layout of a typical 9-person suite with details of double rooms, triple rooms, communal space and toilet facility

Interviewees were asked to complete a questionnaire, shown in Table 3.5, immediately after they woke up. The questionnaire included subjective thermal sensation and satisfaction assessments using ASHRAE seven-point thermal sensation scale and a dichotomous yes/ no question respectively (ASHRAE, 2017), and subjective assessment of sleep quality based on Pittsburgh Sleep Quality Index (PSQI). PSQI is a self-report subjective measure of quality of sleep and sleep patterns by evaluating seven domains including quality, latency, duration, habitual sleep efficiency, disturbances, use of sleep medication, and daytime dysfunction over the past month (Buysse, Reynolds III et al., 1989). To serve the purpose of this investigation, the questionnaire was modified to collect data about sleep quality, latency and disturbance only. Questions relating to use of sleep medication, habitual sleep efficiency and daytime dysfunction were not included as these items were not applicable to the research scope. Instead, subjective questionnaire employed by Lan, Pan et al. (2014) was considered as their study also investigated last-night sleep quality. Questions regarding ease of awakening and sufficient sleep were added into the modified PSQI questionnaire. Sleep quality was therefore assessed by a total of 12 yes/ no questions and an overall sleep quality scale. The global PSQI score was calculated by adding together the score of 13 individual questions. A higher score suggested a better sleep quality.

Table 3.5 Subjective questionnaire for thermal sensations, satisfaction and sleep quality

Thermal sensation vote						
What was your thermal sensation during sleep?						
-3 Cold	-2 Cool	-1 Slightly cool	0 Neutral	+1 Slightly warm	+2 Warm	+3 Hot
Thermal satisfaction						
Were you satisfied with your thermal environment during sleep?						
Satisfied (1)			Dissatisfied (0)			

Sleep quality					
1	I could not get to sleep within 30 minutes last night.	Yes (0)		No (1)	
2	I woke up in midnight and/ or early morning.	Yes (0)		No (1)	
3	I had to get up in the middle of night to use the bathroom.	Yes (0)		No (1)	
4	I had trouble breathing last night.	Yes (0)		No (1)	
5	I coughed and/ or snored loudly last night.	Yes (0)		No (1)	
6	I felt too cold last night.	Yes (0)		No (1)	
7	I felt too hot last night.	Yes (0)		No (1)	
8	I had bad dreams last night.	Yes (0)		No (1)	
9	I had pain last night.	Yes (0)		No (1)	
10	It was easy to wake up this morning.	Yes (1)		No (0)	
11	I felt refreshed right after waking up.	Yes (1)		No (0)	
12	I had enough sleep.	Yes (1)		No (0)	
13	Overall sleep quality	Very good (3)	Fairly good (2)	Fairly bad (1)	Very bad (0)

Thermal load (L) can be expressed by Equations 3.6–3.7, where Q_{sk} is the heat flow from skin, Q_{res} is the heat flow by respiration, $Q_{l,c}$ and $Q_{l,r}$ are the convection and radiation heat loss from outer surface of a clothed body, E_{sk} is the total evaporative heat loss from skin, $Q_{l,sn,res}$ and $Q_{l,e,res}$ are sensible and evaporative heat loss by respiration.

$$L = M - Q_{sk} - Q_{res} \qquad -(3.6)$$

$$L = M - (Q_{l,c} + Q_{l,r} + Q_{l,e,sk}) - (Q_{l,sn,res} + Q_{l,e,res}) \qquad -(3.7)$$

Sensible heat loss from skin is achieved by convection and radiation through clothing, which can be expressed by Equation 3.8, where h_c and h_r are the respective heat transfer coefficient, T_{sk} is the skin temperature, R_{cl} is clothing thermal resistance, f_{cl} is the clothing area factor.

$$Q_{l,c} + Q_{l,r} = \frac{T_{sk} - T_o}{R_{cl} + \frac{1}{f_{cl}(h_r + h_c)}} \qquad -(3.8)$$

For sleeping person in a bedding system, clothing area factor and clothing thermal resistance cannot be determined. Instead, a total thermal resistance (R_t) consisted of the entire bedding system, sleepwear and surrounding air is adopted such that Equation 3.8 is simplified (Lin and Deng, 2008):

$$Q_{l,c} + Q_{l,r} = \frac{T_{sk} - T_o}{R_t} \qquad -(3.9)$$

To evaluate the thermal comfort sensation and satisfaction, Fanger proposed a PMV index with heat balance equations and experimental results collected from climate chamber study, shown in Equation 3.10, where M is the metabolic rate and L is the thermal load on the body defined by the difference between body heat production and heat loss to the surroundings, α is a sensitivity coefficient obtained in the controlled experiment with human subjects conducting activities with various metabolic rates (Fanger, 1970).

$$PMV = \left[0.303e^{-0.036M} + 0.028\right] L = \alpha L \qquad \text{– (3.10)}$$

In Fanger's PMV expression, a seated person is believed to have a metabolic rate of 1 met (58.15 W/m^2). For a sleeping person, metabolic rate drops to 0.7 met (40 W/m^2). Based on the belief that the α value can be applied to activity with lower metabolic rate, and with the assumption of no regulatory sweating during sleep (i.e. skin wittedness (w = 0.06)) (Gagge, Fobelets et al., 1986), T_{sk} = 34.6°C, water vapor pressure in saturated air at T_{sk} (p_{sk} = 5.52 kPa), estimation of $Q_{l,sn,res}$ = 0.0014M(34 – T_a) and $Q_{l,e,res}$ = 0.0173M(5.87 – p_a) (ASHRAE, 2001), Lin and Deng (2008) developed a thermal comfort model for sleeping environment expressed in Equation 3.11, with p_a be the water vapor pressure in ambient air.

$$\begin{aligned} PMV_{sleep} = 0.0998 &\left\{40 - \frac{1}{R_t}\left[(34.6 - T_o) + 0.3762\,(5.52 - p_a)\right]\right\} \\ &- 0.0998\left[0.056\,(34 - T_a) + 0.692\,(5.87 - p_a)\right] \end{aligned} \qquad \text{– (3.11)}$$

Lan, Zhai et al. (2018) developed a two-part model for evaluating the thermal neutrality for sleeping Chinese individuals. In the model, the thermal balance of body parts in contact with the bed and the rest are considered separately. Equation 3.7 is therefore expressed with a coefficient of (1 – ς), which describes the body area that are not in contact with the bed. ς was estimated to be 0.39 for body in supine position (Zhao, Liu et al., 1984, Zhao, Liu et al., 1987). Equation 3.6 is expressed as Equation 3.12 below, where $Q_{l,df,sk}$ and $Q_{l,cod,b}$ are the heat loss by skin diffusion and by conduction through bed, estimated by Equations 3.13–3.14 respectively, with λ be the heat of vaporization of water (2418 kJ/kg at 34°C), D the permeance coefficient of the skin (1.27×10^{-6} g/sm^{2}Pa), $p_{sk,nb}$ the water vapor pressure in saturated air at $T_{sk,nb}$, the mean skin temperature of body not in contact with bed (34.6°C), c the thermal conductivity of bed (0.048 W/m^{2}K), $p_{sk,b}$ the water vapor pressure in saturated air at $T_{sk,b}$, mean skin temperature of body in contact with bed (35.4°C), T_b the surface temperature of bed (assume to be equal to T_a), and t the thickness of bed in meter.

$$\begin{aligned} L = M - [(1-\varsigma)\,(Q_{l,c} + Q_{l,r}) + Q_{l,df,sk} + Q_{l,cod,b}] \\ - (Q_{l,sn,res} + Q_{l,e,res}) \end{aligned} \quad – (3.12)$$

$$Q_{l,df,sk} = \lambda D \times (1 - 0.8\varsigma)\,(p_{sk,nb} - p_a) \quad – (3.13)$$

$$Q_{l,cod,b} = k\varsigma \frac{T_{sk,b} - T_b}{t} \quad – (3.14)$$

Instead of estimating the $Q_{l,sn,res}$ and $Q_{l,e,res}$ according to the ASHRAE handbook, Lan, Zhai et al. (2018) expressed the sensible and evaporative heat loss by respiration by Equations 3.15–3.16, where $\dot{m}$ is the pulmonary ventilation rate of sleeping people (0.128 g/s) (Douglas, White et al., 1982), T_{ex} is the temperature of expired air (34°C), RH_{ex} – RH = 29 – 0.0049p_a is the difference in humidity ratio between expired air and inspired air expressed in McCutchan and Taylor (1951), A_D is the body surface area of Chinese people estimated by Zhao, Liu et al. (1984) and Zhao, Liu et al. (1987).

$$Q_{l,sn,res} = \frac{\dot{m}C_{h,a}\left(T_{ex} - T_a\right)}{A_D} \qquad – (3.15)$$

$$Q_{l,e,res} = \frac{\dot{m}\lambda\left(RH_{ex} - RH\right)}{A_D} \qquad – (3.16)$$

Based on the Equations 3.12–3.16, PMV predicted by 2-part model can therefore be expressed as:

$$\begin{aligned} PMV_{2-part} = {} & 0.0998\left[40 - \frac{13.41 - 1.519p_a - 0.13T_a}{A_D}\right] \\ & - 0.0998\left[1.875 \times (5.52 - p_a) + \frac{0.61 \times (34.6 - T_o)}{R_t}\right] \\ & - 0.0998 \times 0.0187 \times \frac{35.4 - T_a}{t} \end{aligned} \qquad – (3.17)$$

3.5.1. Sleeping thermal condition

A total of 38 sets of environmental data and questionnaires were collected. Since the survey was conducted in winter, air conditionings and fans were not used. Rooms were ventilated naturally with open window. Interviewees had an average of 7.8 hr (SD = 1.2) of sleep, which fell within the recommended sleep duration by National Sleep Foundation, American Academy of Sleep Medicine and Sleep Research Society in the United State. Measurement data taken between 30 minutes after the subject was on bed and 30 minutes before waking up were adopted in data analysis to ensure adaptation to thermal environment. Table 3.6 shows the measurement data of female and male students.

Table 3.6 Measurement data of female and male students

		Female (n = 9)		Male (n = 29)		*p*-value, *t*-test
	unit	Mean	SD	Mean	SD	
Outdoor						
Temperature (T_{out})	°C	18.9	2.1	19.7	2.1	0.41
Relative humidity (RH_{out})	%	85.1	8.2	83.1	10.4	0.58
Indoor						
Air temperature (T_a)	°C	22.3	1.5	23.6	1.9	0.06
Globe temperature (T_g)	°C	22.1	1.6	23.4	1.9	0.07
Radiant temperature (T_{rad})	°C	22.1	1.6	23.4	1.9	0.07
Operative temperature (T_o)	°C	22.2	1.6	23.5	1.9	0.07
Relative humidity (RH)	%	78.2	7.1	72.1	9.8	0.06
Air velocity (v_a)	ms^{-1}	0.0004	0.00026	0.00043	0.00022	0.74
Bedding system						
Clothing value (I_{cl})	clo	4.1	0.6	3.4	1.0	<0.05
Coverage percentage (A)	%	90.4	8.5	80.3	16.4	<0.05

Figure 3.4 shows the clothing values selected by male and female students at different operative temperature. The sizes of the bubbles indicate the coverage percentages. There were well-fit trends of decreasing clothing value (R^2 = 0.88) and coverage percentage (R^2

= 0.75) with increasing operative temperature for male students. No such trends were observed for female students.

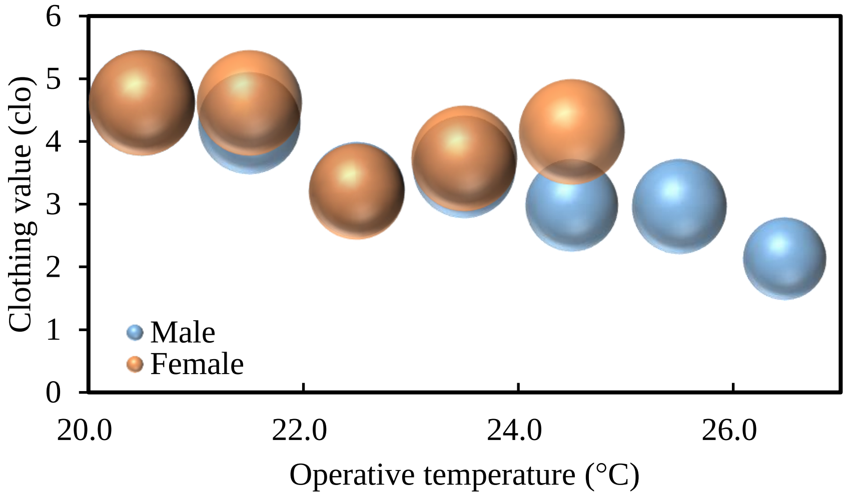


Figure 3.4 Clothing values and coverage percentages selected by students at different operative temperatures

Results suggested some degree of gender difference in sleeping thermal comfort. Although the environmental conditions experienced by students of both genders were statistically the same, the beddings and coverage percentages chosen by female students generally provided a higher total thermal resistance. As females have a 23% lower resting metabolic rate than males due to body mass composition, peak oxygen uptake and gender difference (Arciero, Goran et al., 1993), higher thermal resistance is needed to maintain the core body temperatures. Females are also more sensitive to cool environment, whereas warm environments are less tolerable to males (Pan, Lian et al., 2012).

Besides having different responses towards the same perceived thermal condition due to physiological difference of the two genders, gender-specific psychological difference could also be the cause of distinct choice of bedding systems. A high coverage percentage may provide females with a sense of comfort, as research has linked the use of weighted blanket to improved sleep quality, potentially due to the increase of serotonin, a neurotransmitter that lowers anxiety and produces a calming effects (Gee, Peterson et al., 2016). Male students, on the other hand, would adjust the thermal resistance accordingly for a desired thermal condition for sleep onset. These findings suggested that bedding systems chosen by male students was mainly associated with ambient thermal conditions, while female students would select the preferred thermal insulation according to their own preferences in addition to thermal needs.

3.5.2. Subjective thermal sensations and thermal comfort model predictions

Thermal comfort was evaluated by TSV, thermal satisfaction and the two above-mentioned sleeping thermal comfort models. Table 3.7 shows the measurement data of thermally satisfied and dissatisfied groups of students. Results suggested that thermal satisfactions were sensitive to operative temperature. Significant differences were found in TSV and $PMV_{2\text{-part}}$ of the two groups but not PMV_{sleep}. Both sleeping thermal comfort models overestimated the thermal sensations of students during sleep, surprisingly with negative correlations given by Equations 3.18–3.19. Figure 3.5 demonstrates the correlations between TSV, PMV_{sleep} and $PMV_{2\text{-part}}$; Figure 3.6 shows the relationship between TSV/ PMVs and selected total clothing values.

$$TSV = -7.2PMV_{2-part} + 9.5, \quad R^2 = 0.60 \qquad \text{– (3.18)}$$

$$TSV = -4.2PMV_{sleep} + 4.7, \quad R^2 = 0.75 \qquad \text{– (3.19)}$$

Table 3.7 Thermal sensation results by satisfied and dissatisfied groups

	Satisfied (n = 23)		Dissatisfied (n = 15)		*p*-value,
	Mean	SD	Mean	SD	*t*-test
Indoor					
Operative temperature (T_o)	23.9	1.7	22.2	1.7	<0.05
Air velocity (v_a)	0.0004	0.00028	0.0005	0.00012	0.39
Bedding system					
Clothing value (I_{cl})	3.5	1.0	3.7	0.9	0.72
Coverage percentage (A)	82.9	14.9	82.4	16.3	0.92
Thermal Vote					
$\lvert TSV \rvert$	0.4	0.6	1.5	0.5	<0.05
$\lvert PMV_{sleep} \rvert$	1.4	1.5	1.1	0.5	0.17
$\lvert PMV_{2\text{-part}} \rvert$	1.5	0.2	1.3	0.3	<0.05

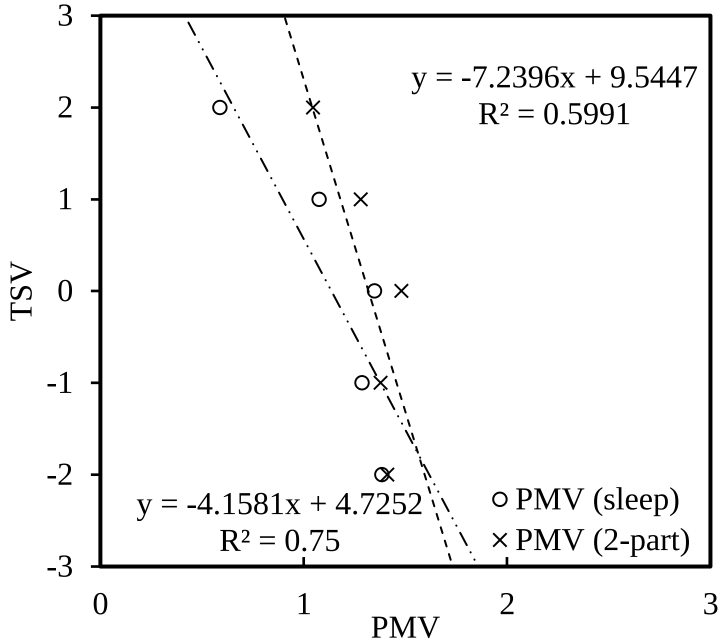


Figure 3.5 Correlations between TSV and PMVs by selected sleeping thermal comfort models

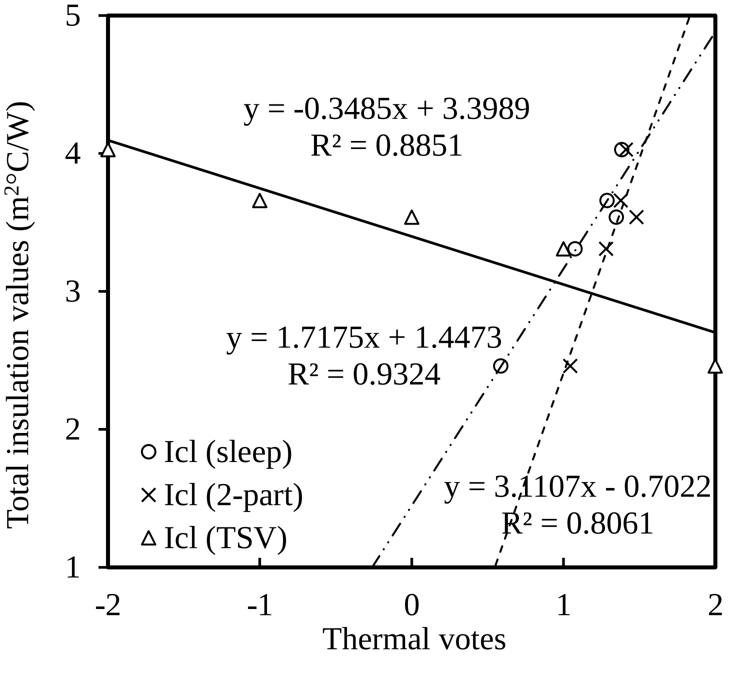


Figure 3.6 Correlations between TSV/ PMVs and selected total clothing values

Figure 3.7 exhibits a positive correlation between TSV and operative temperature, with $R^2 = 0.73$, suggesting subjective thermal sensation was sensitive to the change in ambient thermal condition. In order to determine the preferred T_n for sleeping young adults, interviewees were divided into Group –: voted for a cool TSV (prefer warmer; n = 19) and Group +: voted for a warm side TSV (prefer cooler; n = 5). Figure 3.8 shows the percentiles ϕ of the two groups at various operative temperatures approximated by normal distributions. From the result, T_n for sleeping university students was determined as 23.05°C, where the two lines intercept with each other, i.e. $\phi_{-}|_{To} = \phi_{+}|_{To}$. Alternatively, T_n can be computed simply by taking the average of operative temperatures which the interviewees had a neutral thermal sensation (i.e. TSV = 0), which was 23.81°C with average I_{cl} = 3.54 clo.

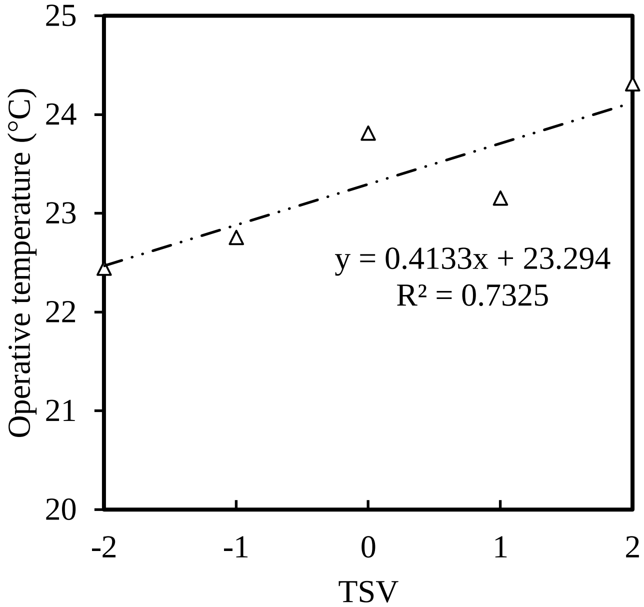


Figure 3.7 Correlation between TSV and operative temperatures

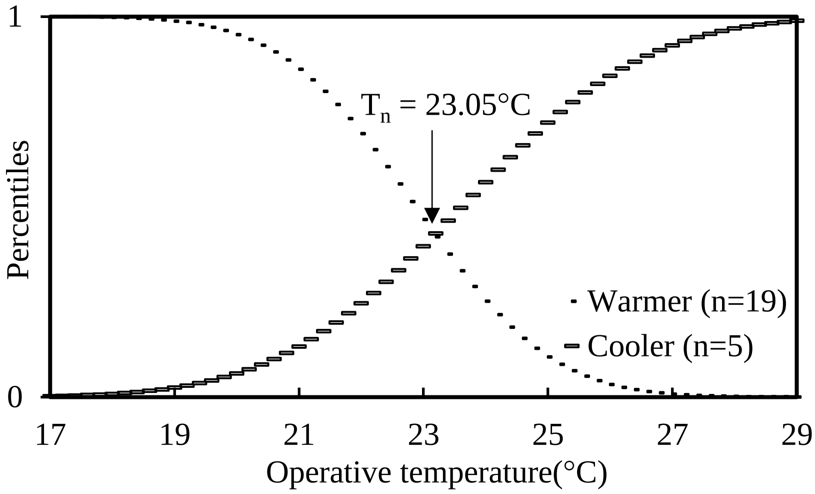


Figure 3.8 Neutral temperature of university students with average I_{cl} = 3.58 clo and M = 0.7 met

Subjective sensation results showed that existing models cannot accurately predict actual thermal sensations. TSV was, unexpectedly, found to be negatively correlated with the PMVs predicted by selected models. Figure 3.7 exhibits a strong positive correlation between total insulation values and PMVs, indicating that PMVs given by both prediction models depended largely on the total clothing values.

On the other hand, TSV was negatively associated with clothing values, which seems to be unorthodox to thermal comfort belief, given that a positive correlation between TSV and operative temperature was observed and shown in Figure 3.8. The results concurred with studies that observed dissimilar physiology in sleeping and awakening state. Jennings, Reynolds III et al. (1993) suggested that thermal sensitivity is greatly reduced during REM compared to NREM stage and wakefulness. Sweat onset is delayed and sweat rate is decreased during REM, leading to a reduced heat dissipation by evaporation and heat tolerance (Sagot, Amoros et al., 1987). Moreover, a constant skin temperature was assumed in the models. Skin temperature variation has been found to play a crucial role in heat dissipation for sleep onset, acting as an input signal for sleep regulation and maintaining SWS (van Someren, 2000). These findings indicated that conventional belief of thermal load is not applicable to sleeping person. Parameters in relation to heat flow and heat loss from body during sleep with bedding system are therefore needed to be identified by experiment.

In addition to the difference between thermal load due to dissimilar physiology in sleeping and awakening state, behavioral thermoregulations during sleep cannot be explained by physical sleeping thermal comfort models. Clothing values of bedding systems estimated by immobile thermal manikin (Lin and Deng, 2008) are not able to reflect the actual thermal resistance since sleeping person may adjust his posture throughout the night. During awakening state, constant adjustment of clothing insulation can be done according to thermal condition to maintain a neutral thermal sensation. During sleeping state, one may adjust the coverage percentage of body, especially on area with higher thermal sensitivity, according to changing indoor temperature (Okamoto-Mizuno, Tsuzuki et al., 2003). Sleeping individual may also change from supine position to lateral position when the bed climate is hot, allowing effective local cooling of back by heat dissipation in proximal area (Qian, Lan et al., 2017). It is therefore necessary to explore further on clothing insulations and behavioral adjustments during sleep in order to determine the sleeping thermal sensation.

Besides, existing sleeping thermal comfort models may overestimate the effect of ambient thermal conditions on sleeping thermal sensations. Even though a positive correlation between operative temperature and TSV was observed, multiple studies have suggested that bed microclimate has a greater effect on thermal comfort and sensations during sleep period than ambient thermal conditions (Song, Liu et al., 2015, Wang, Liu et al., 2015). Bischof, Madsen et al. (1993) illustrated from experiment that large variation in bedding microclimate could exist even under the same ambient conditions. Therefore, a comprehensive approach would be to study the bedding environment as a whole rather than the ambient environment.

T_n given in this investigation (23.05°C or 23.81°C) agreed with the sleeping thermal comfort study conducted in winter by Pan, Lian et al. (2012), which suggested that at the given bedding system similar to this one, 23°C was the optimal condition for shortest sleep latency and maintaining deep sleep. However, this T_n was much higher than the comfort temperature (<18°C) predicted by both sleep thermal comfort models at 3.58 clo. The underestimated T_n by models echoed with the overestimation of thermal sensations. The discrepancies may be due to the assumption in the models that the sleeping thermal comfort requirement (i.e. α value) can be extrapolated to a lower metabolic rate of 40 W/m^2. This linear relationship between thermal load and thermal sensation may even be incorrect, as suggested by many research focusing on physiological responses towards thermal conditions, responses towards cold and hot exposure of an individual are asymmetrical (Okamoto-Mizuno and Mizuno, 2012).

A recent experimental study of local body thermal condition for sleeping comfort suggested that the thermal sensation in sleeping state and waking state were different under the same thermal environment (Song, Liu et al., 2020). Lan, Pan et al. (2014) also found that under the same thermal environment, subject's thermal sensations decreased when they were asleep. The difference in thermal sensation may be explained by the decrease in core body temperature during sleep induced by underlying circadian rhythm that allows greater blood flow to the skin, thus enhancing heat loss to the environment (Kräuchi, Cajochen et al., 1999). In addition, local body cooling at back and head were found to effectively improve thermal comfort and sleep quality in hot environments (Lan, Qian et al., 2018). All these findings indicated that thermal sensation during sleep is distinct and localized. It is essential for sleeping thermal comfort model to address the discrepancies.

3.5.3. Sleep quality and thermal comfort

Sleep quality of students were evaluated by a modified PSQI questionnaire consisted of 13 questions and an aggregate global PSQI score. Questions 4–9 recorded a less than 5 "Yes (0)" count. Majority of the interviewees had problems with sleep latency (Q1: 31.6%), mid-sleep/ early awakenings (Q2: 52.6%), difficulty waking up (Q10: 42.1%) and tiredness after waking up (Q11: 36.8%). It is noteworthy that the students had an average of 7.8 hr of sleep during the measurement, which were deemed adequate for this age range. Sleep problems identified by interviewees could indicate poor sleep quality caused by environmental factors. Associations between individual questions with meaningful sample size (i.e. both Yes and No count ≥ 5) (Q1–3, 10–12) and self-assessed overall sleep quality (Q13) were evaluated using point-biserial correlation. Table 3.8 exhibits the point-biserial correlation coefficient (r_{pb}) which measures the strength of association, and *p*-value by *t*-test. It was concluded that self-assessed overall sleep quality was positivity correlated with mid-sleep/ early awakenings, refreshment and duration of sleep.

Table 3.8 Associations between individual sleep aspects and overall sleep quality

	Q1	Q2	Q3	Q10	Q11	Q12
Sleep problem	sleep latency	mid-sleep/ early awakenings		ease for waking up	refreshment	duration
r_{pb}	0.24	0.46	0.36	0.3	0.58	0.39
p-value, *t*-test	0.14	<0.005	<0.05	0.06	<0.005	<0.05

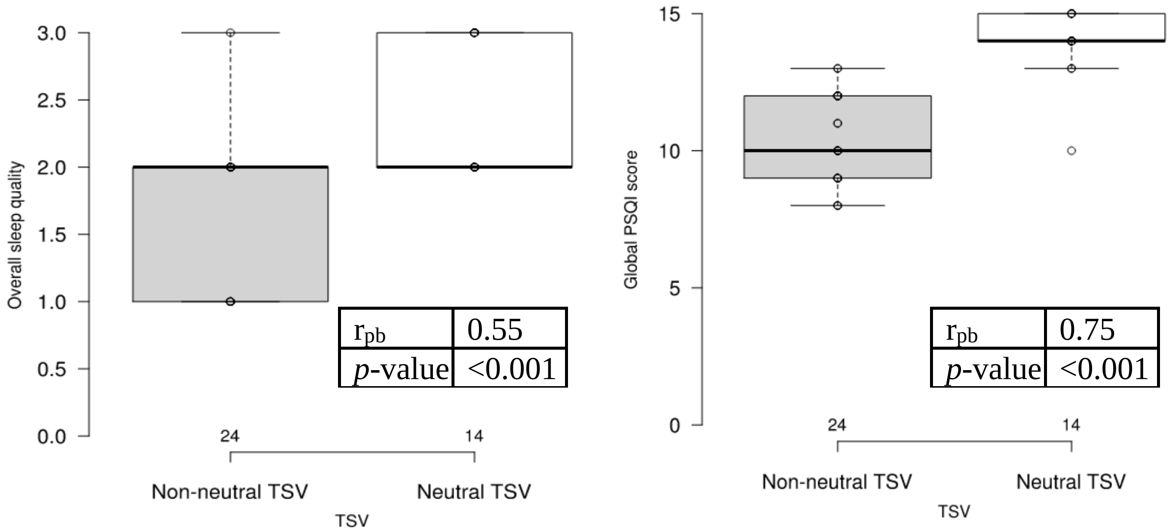
To find out the effect of thermal environment on sleep quality, data were categorized into groups for analysis. The first comparison was done between sleep quality data collected from students with neutral TSV (TSV = 0) and those without (TSV = -2/-1/+1/+2), and the second was between sleep quality data collected from interviewees who were thermally satisfied with the environment and those who were dissatisfied. Table 3.9 describes the data in each group. Results suggested that when people had a neutral TSV, they tended to be thermally satisfied (= 0) than those who voted the rest. Self-assessed overall sleep quality and global PSQI score were also significantly higher if they had a neutral TSV. It was also found that thermally satisfied group had significantly higher self-assessed overall sleep quality and global PSQI score. Figure 3.9 shows the boxplots of overall sleep quality and global PSQI score of non-neutral/neutral TSV group and dissatisfied/satisfied groups. Associations between thermal sensation/satisfaction and overall sleep quality/global PSQI score were indicated by point-biserial correlation coefficient shown in the figure.

Interestingly, students voted for a cool TSV (TSV = -2/-1) had slightly higher average global PSQI score and thermal satisfaction than those who voted for a warm TSV (TSV = +1/+2) (*p*-value, *t*-test = 0.05). Figure 3.10 exhibits the relationships between TSV, average global PSQI score and thermal satisfaction.

Table 3.9 Thermal sensations, thermal satisfaction and sleep quality

	TSV = 0 (n = 14)		TSV = -2/-1/+1/+2 (n = 24)		*p*-value, *t*-test
	Mean	SD	Mean	SD	
Thermal satisfaction	1	0	0.38	0.48	<0.001
Overall sleep quality	2.43	0.49	1.71	0.54	<0.001
Global PSQI score	13.86	1.25	10.46	1.58	<0.001
	Satisfied (n = 23)		Dissatisfied (n = 15)		*p*-value, *t*-test
	Mean	SD	Mean	SD	
Overall sleep quality	2.30	0.46	1.47	0.50	<0.001
Global PSQI score	13.09	1.47	9.6	1.25	<0.001

(a)



(b)

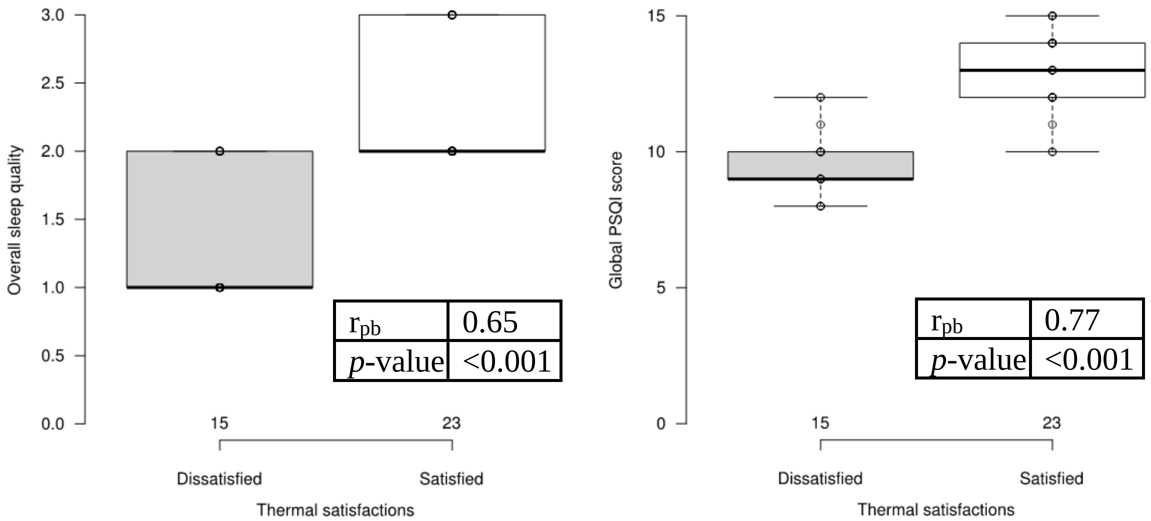


Figure 3.9 Overall sleep quality and global PSQI score of (a) neutral and non-neutral TSV groups; and (b) thermally dissatisfied and satisfied groups

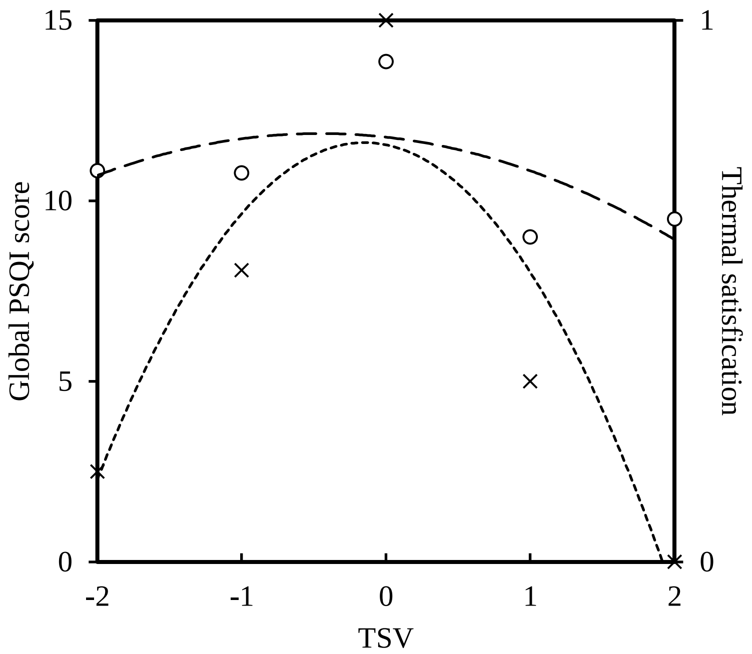


Figure 3.10 Average global PSQI score and thermal satisfaction at various TSVs

Many have discussed the correlation between ambient temperature and sleep quality with diverse results and opinions. However, discussing sleep quality only with ambient temperature may not be appropriate as positive effects of bed cover and quilt on cold exposure are often ignored. Bedding system can sustain an isolated high temperature bed microclimate for maintaining high level of skin blood flow and skin temperature, leading to better thermal sensation in cold exposure (van Someren, 2000). Because of the above-mentioned reasons, in this investigation, association between thermal comfort and sleep quality was investigated instead of ambient temperature. Both thermally satisfied students and students with neutral thermal sensation had significantly higher self-assessed overall sleep quality and global PSQI score, with statistically significant positive associations indicated by point-biserial correlation coefficients, suggesting that sleep quality was largely influenced by thermal comfort.

Average global PSQI score and thermal satisfaction at various TSV (Figure 3.10) indicated that students who felt cold were less dissatisfied and had a better sleep quality than those who felt hot. This result revealed an interesting phenomenon that sleeping people have different physiological and psychological reactions towards hot and cold environments. In fact, mixed viewpoints towards the effects of cold and heat exposure on sleep quality were concluded from various studies, which can be caused by difference in experimental characteristics including subject's ethnicity and climate (Buguet, 2007). Some research suggested that cold exposure disrupts sleep more than heat exposure for naked subject (Lan, Tsuzuki et al., 2017). However for subjects with bedding system, increased toleration to cold air and improved sleep quality were observed (Tsuzuki, Mori et al., 2015). A number of studies found no significant difference in sleep quality with temperatures ranging from 9°C to 20°C (Okamoto-Mizuno, Tsuzuki et al., 2009), 13°C to 23°C (Muzet, Libert et al., 1984) and 3°C to 17°C (Okamoto-Mizuno and Tsuzuki, 2010), suggesting with adequate clothing insulation to maintain a constant bed climate, cold exposure does not affect sleep much.

With bedding system, heat exposure may pose more disturbance to sleep than cold exposure (Okamoto-Mizuno and Mizuno, 2011). In heat exposure at about 35°C, shortened sleep duration and increased wakefulness was observed (Libert, Di Nisi et al., 1988). It is also common to see a decrease in SWS and REM in hot sleeping environments (Karacan, Thornby et al., 1978). People may adopt behavioral thermoregulation to reduce heat stress, for example changing sleeping posture, use of air flow, etc. (Tsuzuki, Okamoto-Mizuno et al., 2008). However, these behavioral thermoregulations in mid-sleep indicate wakefulness and therefore degrading the sleep quality.

3.6. Summary

Current research gaps in thermal comfort modelling are discovered. The discrepancies found between the actual thermal comfort field data and PMV/PPD model predictions indicate a potential risk of misusing the inaccurate model for research and practical uses. The subsequent errors incurred by the use of incorrect thermal comfort predictions can lead to substantial uncertainties in energy estimations and satisfaction evaluations.

In spite of the fact that the PMV/PPD model may not be able to accurately evaluate thermal comfort, it is still being used as the basis of most thermal comfort research, especially for research related to indoor environment simulation and system control.

This chapter also identifies dormitory sleeping thermal conditions, sensations, satisfaction and sleep quality. Under the same thermal environment, females generally opt for a bedding system with higher total thermal resistance, which may not be for the purpose of maintaining body temperature, but instead for a sense of comfort and better sleep quality. Current thermal sensation prediction models based on heat balance of human body, a similar approach to Fanger's PMV model, overestimates the thermal sensations and underestimates the T_n, suggesting the PMV expression is not be applicable to sleeping individuals due to differences in thermal sensation to thermal conditions in sleeping and awakening state, possibly caused by dissimilar physiology in the two states, behavioral thermoregulations during sleep, overestimation of the effect of ambient conditions on sleeping thermal sensation, asymmetrical thermal responses towards cold and hot exposure and localized thermal sensation during sleep. Both thermally satisfied students and students with neutral thermal sensation have significantly better self-assessed sleep quality, suggesting thermal comfort largely influences sleep quality.

Sleeping thermal comfort survey demonstrates the importance of identifying and maintaining different thermal comfort requirements for different kinds of daily activities. Consistent and unified building thermal conditions and thermal comfort models may not be suitable for all settings.

In order to reduce the uncertainties caused by inaccurate model input, minimizing the disagreement between actual dissatisfaction and predicted dissatisfaction is of utmost importance. Before a model that can truly represent thermal comfort, sensation and acceptance is available, the PMV/PPD representation shall at least be updated accordingly using field data gathered from worldwide research efforts to minimize the performance gap of the PMV/PPD model.

Chapter 4. Evaluation and improvement of IEQ modelling

4.1. Introduction

Modern people stay indoor most of the time. IEQ has become a major concern for sustainable development as it affects occupant's health and well-being as discussed before. IEQ problems shall be addressed at design stage and throughout the lifecycle of the building to protect the occupants (Al horr, Arif et al., 2016). IEQ acceptance prediction models therefore are important and useful for building designers and facility management when making decisions regarding the building performance.

Physical environmental parameters such as thermal environment, acoustics, air quality and lighting are all interrelated and associated with occupant comfort. An integrated subjective-objective approach is often used to address IEQ by multivariate-logistic regression models, which define IEQ in a 2-fold process, occupant responses towards individual IEQ aspects and to the overall IEQ, i.e. a double layer logistic model. Multivariate-logistic model for IEQ acceptance for various environments have been developed based on occupant's acceptance on four environmental aspects, namely IAQ, thermal, aural and visual comfort. The models can be used as quantitative assessment criteria for similar environments where various human response factors matter (e.g. occupant comfort, well-being, health and productivity).

To identify the discrepancies between predictions by pre-established subjective-objective models and actual field responses, in this chapter, IEQ responses from occupants living in very small residential units are investigated objectively and subjectively. Results allow us to understand the effects of perception, adaption and tolerance on subjective IEQ responses in extreme environment, which provide insights into improving existing IEQ assessment models by incorporating subjective responses collected in field.

A reliable IEQ model with robust predicting ability and small discrepancies between predicted and actual acceptance is crucial to sustainable building development (Andersen, Fabi et al., 2016). On top of that, model updating to minimize the difference between additional measured data and predictions is also highly preferred (Lam, Zhao et al., 2014).

In this chapter, based on available field data in literature, an open probabilistic IEQ acceptance model that uses frequency distribution functions of occupant’s responses towards four major IEQ parameters (i.e. thermal comfort, IAQ, aural and visual comfort) is also proposed and developed. The aim is to provide another comfort modelling method for occupant’s acceptance prediction which allows simpler model updating with frequency distributions used, and is more robust in reflecting occupant’s psychological perception towards the indoor environment. The proposed model is free from assumptions of regressions and is flexible to a diverse range/ types of IEQ parameters as well as to the inclusion of new parameters.

4.2. Overview of very small residential units

Rapid population increase and urbanization have promoted the migration from rural and suburban areas to urban cities, more and more small houses and high-rise multi-unit residential buildings will be developed in cities (Andargie, Touchie et al., 2019). It is a known fact that high occupancy density has the effect of magnifying the variability of environmental conditions, our understandings on IEQ in residential environments shall be enhanced and updated. As the extreme environmental conditions in a very small living environment are unbearable to most people, responses of those living under such conditions to IEQ may not follow the trends described in other studies on IEQ acceptance in residential environments.

Hong Kong, a metropolitan city of over 7 million inhabitants, has been facing a housing shortage for years due to limited land supply. In recent years, as housing price kept rising, some very small living environments have emerged as affordable choices of accommodation. These spaces include temporary shelters, rooftop structures, bedspaces, cocklofts and subdivided units (SDUs), and are usually high in occupancy density and poor in hygiene (Lai, Lee et al., 2017). According to CUHK (2015), the average per capita living area for these environments is 4.44 m^2ca^{-1}, which is much smaller than the minimum living standards for USA (14 m^2ca^{-1}), Japan (19 m^2ca^{-1}), Taiwan (7 m^2ca^{-1}), South Korea (12 m^2ca^{-1}) and Hong Kong (6.5 m^2ca^{-1}) (CPA, 2008). It was estimated that there were over 199,900 residents living in approximately 90,000 small residential units in Hong Kong (CSD, 2016).

Figure 4.1 illustrates some examples of typical SDUs by government report (CSD, 2016). Figure 4.1(a) shows examples of SDUs partitioned from an apartment of 5 m × 20 m. The example units are equipped with private toilets and independent cooking space in an area of about 7–10 m^2. Figure 4.1(b) demonstrates an SDU created in the quarter on 3/F by newly constructed wall with a wall opening (4/F plan shows no alteration for comparison). The unit can be further sub-divided into smaller units by additional walls and openings as shown in Figure 4.1(c).

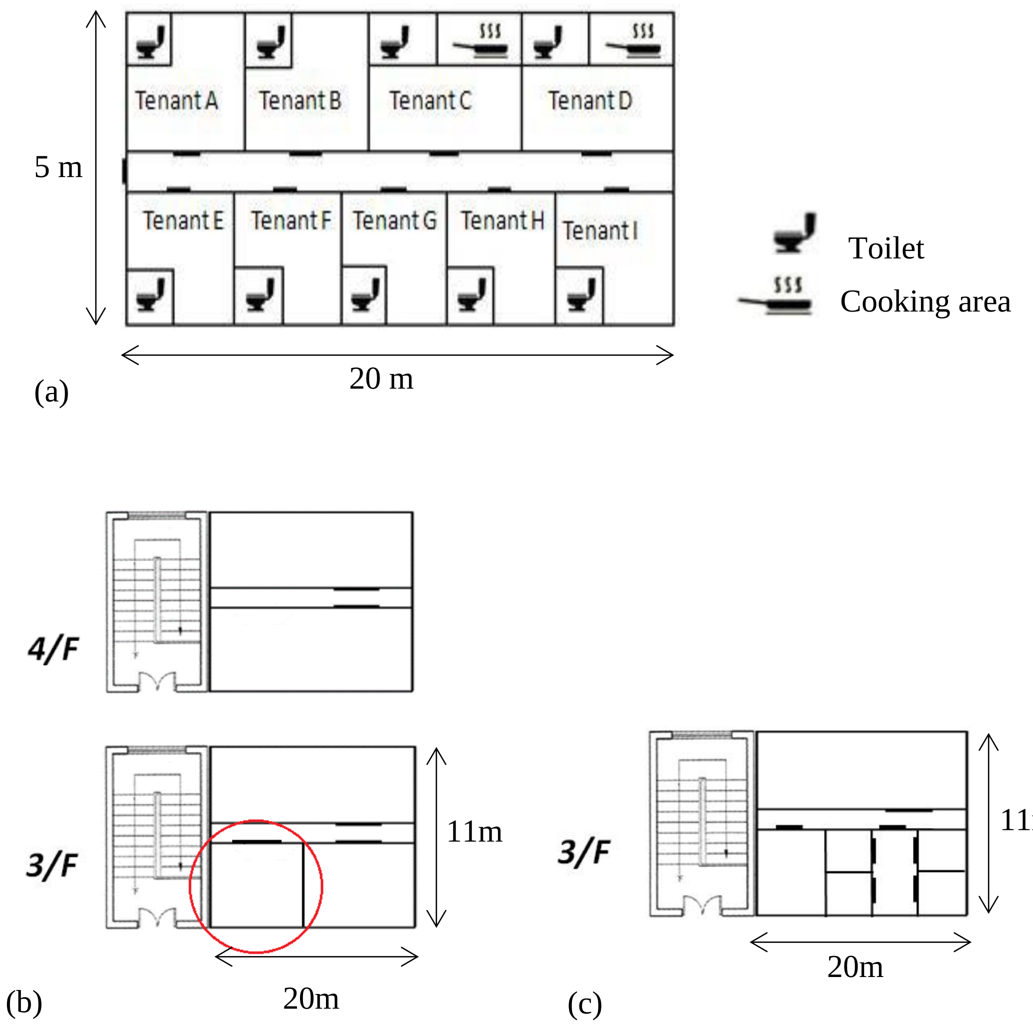


Figure 4.1 Example arrangement of subdivided units (SDUs)

4.3. Survey of IEQ in very small residential units (SDUs)

Subjective IEQ responses and on-site field measurements were collected through individual interviews conducted in small residential units in Hong Kong from October to December 2016. A total of 52 residents were interviewed: 8 living in single units, 37 in refurnished SDUs, 1 in a bedspace unit and 6 in rooftop houses. Resident's I_{cl} and M at the time of interview were determined using ASHRAE Standard 55 (ASHRAE, 2010). The single units and rooftop houses were in general bigger in size with floor area about 18.6–37.2 m^2; SDUs and bedspace were smaller with floor area of 6.0–18.6 m^2.

In order to make direct comparison with previously developed IEQ model for residential buildings (Lai, Mui et al., 2009), T_a, T_{rad}, v_a, RH were measured by Lutron Heat Index WBGT Meter (WBGT–2009) and Lutron Hot Wire Anemometer (AM–4204HA) for evaluating the thermal environment using PMV, CO_2 by TSI Q–Trak IAQ Monitor (TSI–8551), horizontal illuminance level by Lutron Digital Lux Meter (LX–1108) and equivalent noise level by Lutron Digital Sound Level Meter (SL–4001) for determining the IAQ, quality of visual and aural environments respectively. Since most of the interviewed living spaces were extremely small and without partitioning, a 15-min physical measurement was carried out in each unit, which was considered to be 'steady' enough for assessing occupant's response to perceived indoor environmental factors. This protocol was also adopted in previous study (Lai, Mui et al., 2009).

Interviewees were invited to rate thermal sensations via a seven-point semantic differential thermal sensation scale (-3: Cold, -2: Cool, -1: Slightly cool, 0: Neutral, +1:

Slightly warm, +2: Warm, +3: Hot) (ASHRAE, 2010). In addition, they were asked to evaluate IAQ acceptance via a five-point scale: very good, good, neutral, bad and very bad. Aural comfort and visual comfort were assessed using a maximum of 100 marks.

To validate the differential responses, a direct polar acceptable/ unacceptable question “Is the thermal environment/ indoor air quality/ aural environment/ visual environment of the indoor living environment perceived by you satisfactory?” was asked alongside the differential questions (Portney and Watkins, 2009). Validation was based on the consistency of the answers to the differential and polar questions. For the thermal environment differential scale, TSV = -3/ -2/ +2/ +3 were considered as unacceptable, and TSV = -1/ 0/ +1 as acceptable. For IAQ, very good, good and neutral were acceptable, while bad and very bad were unacceptable. If the respondent voted unacceptable for the differential question but voted satisfactory for the polar question, the contradictory response was considered as invalid. Extreme cases (e.g. an acceptable visual environment with a score of 0) were also considered to be invalid. Finally, they were required to determine the satisfaction towards the overall IEQ.

4.3.1. General environmental condition

52 per capita apartment areas were surveyed, with size ranging from 2.3 to 16.3 $m^2\ ca^{-1}$, 5.7 $m^2\ ca^{-1}$ on average. The average value was comparable to the average size of SDUs of 5.8 $m^2\ ca^{-1}$ found in a former research by the government (p-value > 0.05, t-test) (CSD, 2016), which was well below the Hong Kong average living space of 13.1 $m^2\ ca^{-1}$ (p-value < 0.0001, t-test) by Hong Kong Housing Authority (HKHA, 2016). Most of the apartments were equipped with window-type air-conditioner, but 85% of them were not operating during the interview. Ambient weather condition was recorded with an average outdoor T_a of 26.9°C (SD = 2.2) and RH of 71.3% (SD = 13.5).

Table 4.1 summarizes the number of votes on acceptance towards the overall IEQ and the four environmental aspects. Votes made in the previous study are shown alongside for comparison (Lai, Mui et al., 2009). Only slightly more than half (62%) of the respondents were satisfied with the overall IEQ in their homes, given that over 95% of residents in average residential buildings showed satisfaction. Regarding the four environmental aspects, satisfaction votes were much lower in small units than average houses. A significantly different voting pattern was observed (p-value < 0.0001, Chi-square test).

Table 4.1 Votes on IEQ acceptance

	Overall IEQ		Thermal		IAQ		Visual		Aural	
vote	0	1	0	1	0	1	0	1	0	1
Very small residential units	20	32	25	27	28	24	18	34	20	32
Average residential buildings	9	166	13	112	7	118	10	115	12	113

Table 4.2 presents the measurement results of physical parameters in average residential buildings (Lai, Mui et al., 2009) and very small residential units. Small variations over the 15-min measurement period suggested a 'steady' environment for investigation. PMV index proposed by Fanger (1970) was determined using environmental parameters – T_a, T_{rad}, v_a, RH, and two occupant parameters – I_{cl} and M. Significant differences between small unit residents being unsatisfied and satisfied with overall IEQ were observed in a number of thermal parameters, including PMV, T_a, T_{rad} and T_o (p-value < 0.05, t-test), indicating the residents were sensitive to thermal environment.

As it can be seen that no significant differences were observed in all temperatures (i.e. T_a, T_{rad} and T_o) and the average horizontal illuminance levels, the thermal and visual environments of both living environments were comparable. Although there were significantly higher PMV in small units possibly due to higher M and thus lower I_{cl} to achieve thermal comfort, the differences in PMV between voting groups of the two environments were insignificant.

Some very small units were found to have no or only very small openable windows, therefore they were poorly natural-ventilated. As a result of higher occupancy density and poor ventilation, the average CO_2 (1,046ppm) and average v_a ($0.2ms^{-1}$) recorded in very small units were significantly higher and lower than those reported in average residential units (675ppm and $0.37ms^{-1}$ respectively). In contrast, the average equivalent noise level in small unit was significantly lower than the average houses.

Table 4.2 Measurement results of indoor environmental parameters for average residential buildings (Lai, Mui et al., 2009) and very small residential units

Parameter		Average residential buildings	Very small residential units	*p*-value, *t*-test
Per capital area (m^2)		13.1	5.7 (3.4)	<0.0001
Predicted mean vote (PMV)		0.27 (0.88)	0.56 (0.82)**	<0.05
	Unsatisfied	0.65 (0.95)	0.94 (0.43)	0.43
	Satisfied	0.24 (0.86)	0.32 (0.92)	0.65
Air temperature T_a (°C)		27.3 (2.2)	27.4 (2.2)**	0.81
	Unsatisfied	28.1 (2.3)	28.3 (1.2)	0.86
	Satisfied	27.3 (2.2)	26.9 (2.5)	0.43
Radiant temperature T_{rad} (°C)		27.5 (2.0)	27.3 (1.8)**	0.63
	Unsatisfied	28.1 (2.4)	28.2 (1.2)	0.94
	Satisfied	27.4 (1.9)	26.8 (2.0)	0.12
Air velocity v_a (ms^{-1})		0.37 (0.2)	0.2 (0.19)	<0.05
	Unsatisfied	0.49 (0.3)	0.18 (0.2)	<0.05
	Satisfied	0.36 (0.2)	0.21 (0.2)	<0.05
Operative temperature T_o (x_1) (°C)		27.4 (2.0)	27.3 (2.0)**	0.93
	Unsatisfied	28.1 (2.4)	28.2 (1.2)	0.91
	Satisfied	27.3 (2.0)	26.9 (2.2)	0.25
Relative humidity RH (%)		83.9 (10.5)	73.5 (12.3)	<0.05
	Unsatisfied	84.1 (10.3)	76.1 (10.3)	0.09
	Satisfied	83.9 (10.4)	71.8 (13.2)	<0.05
Metabolic rate M (Met)		1.06 (0.11)	1.13 (0.10)	<0.05
	Unsatisfied	1.11 (0.13)	1.15 (0.09)	0.45
	Satisfied	1.05 (0.10)	1.12 (0.10)	<0.05
Clothing value I_{cl} (clo)		0.48 (0.11)	0.40 (0.11)	<0.05
	Unsatisfied	0.48 (0.11)	0.39 (0.10)	<0.05
	Satisfied	0.48 (0.11)	0.41 (0.12)	<0.05
Carbon dioxide (x_2) (ppm)		675 (328)	1046 (500)	<0.05
	Unsatisfied	497 (345)	1240 (609)	<0.05
	Satisfied	689 (327)	925 (369)	<0.05
Horizontal illuminance level (x_3) (lux)		187 (273)	191 (127)	0.88
	Unsatisfied	307 (435)	156 (112)	0.36
	Satisfied	178 (252)	213 (131)	0.29
Equivalent noise level (x_4) (dBA)		67.3 (6.2)	62.6 (4.8)	<0.05
	Unsatisfied	70.6 (7.9)	62.4 (5.0)	<0.05
	Satisfied	67.1 (6.0)	62.8 (4.7)	<0.05

Remark: Standard deviation in brackets; *t*-test between satisfied and unsatisfied groups of residents in very small residential units for each indoor environmental parameter, where **–*p*-value ≤ 0.05.

4.3.2. Acceptance of thermal, IAQ, visual and aural environments

18 voted for neutral (0), 8 voted for slightly warm (+1) and 24 voted for hot (+3), with no votes for cold side (-3–-1) and warm (2). Respondents living in small unit demonstrated a similar thermal sensation pattern to those in average houses – skewed towards the warm side. The TSV against PMV is given by Equation 4.1 ($R = 0.72$, p-value < 0.05, t-test).

$$TSV = 2.79PMV + 0.12, \qquad 0 \leq TSV \leq 3 \qquad \text{– (4.1)}$$

Both living environments reported a narrower thermal acceptability range (slopes of 2.2 and 2.79 respectively) than the Fanger's PMV model. Besides, the occupants of small units preferred a slightly cool environment as a thermal neutral setting, i.e. PMV = -0.12 at TSV = 0 (PMV = -0.15 in the average houses). This outcome suggested that small unit occupants were more sensitive to heat and tended to be dissatisfied with a hot environment, despite the environmental conditions were in fact comparable to the average living environments.

Figure 4.2 graphed the correlation between PMV and thermal acceptance. Thermal acceptance in warm environments was skewed to the cool side, indicating a preference for slightly cool environment. Given a hot environment (i.e. PMV ≥ 2), there was still some degree of acceptance as compared to zero acceptance beyond PMV = 1.5 in average houses, suggesting that occupants of small units, although were more sensitive to warmth, they have already developed some level of tolerance to the hot environment.

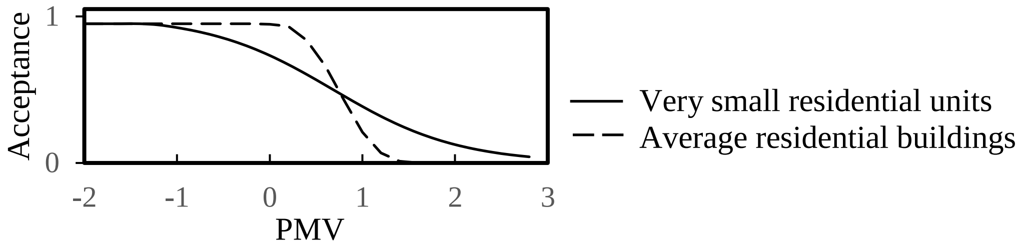


Figure 4.2 Acceptance of PMV in living environments

Figure 4.3(a) illustrates thermal acceptance (δ_1) as a function of T_o. Greater sensitivity to variation of T_o than the average houses were observed. The acceptance was only 0.09 for T_o = 32°C, which was much lower than the value of 0.74 for average residential buildings. Figures 4.3(b)–4.3(d) exhibit the acceptance for CO_2 (δ_2), horizontal illuminance level (δ_3) and equivalent noise level (δ_4). Since occupant's responses specific to each of these independent factors were collected, it was assumed that occupant's acceptance of one aspect was solely dependent on the surrogate parameter of that aspect. In general, higher level of illuminance, lower levels of CO_2 and equivalent noise were preferred. Acceptance variabilities for these three aspects were very small over the ranges of δ_2 = 0.53–0.22 for CO_2 of 800–1800ppm, δ_3 = 0.62–0.70 for horizontal illuminance levels of 10–500lux, and δ_4 = 0.66–0.54 for equivalent noise levels of 50–80dBA. The very flat curves in the figures reflected that small unit occupants were more concerned about the thermal aspect and less emphasized on the other three aspects. Table 4.3 summarizes the regression constants given by Equation 4.2.

$$\delta_0 = 1 - \frac{1}{1 + e^{C_{0,0} + \sum_i (C_{i,0} x_i)}};$$
$$\delta_i = 1 - \frac{1}{1 + e^{C_{0,i} + C_{1,i} x_i}}; \qquad i = 1, 2, \cdots 4 \qquad -(4.2)$$

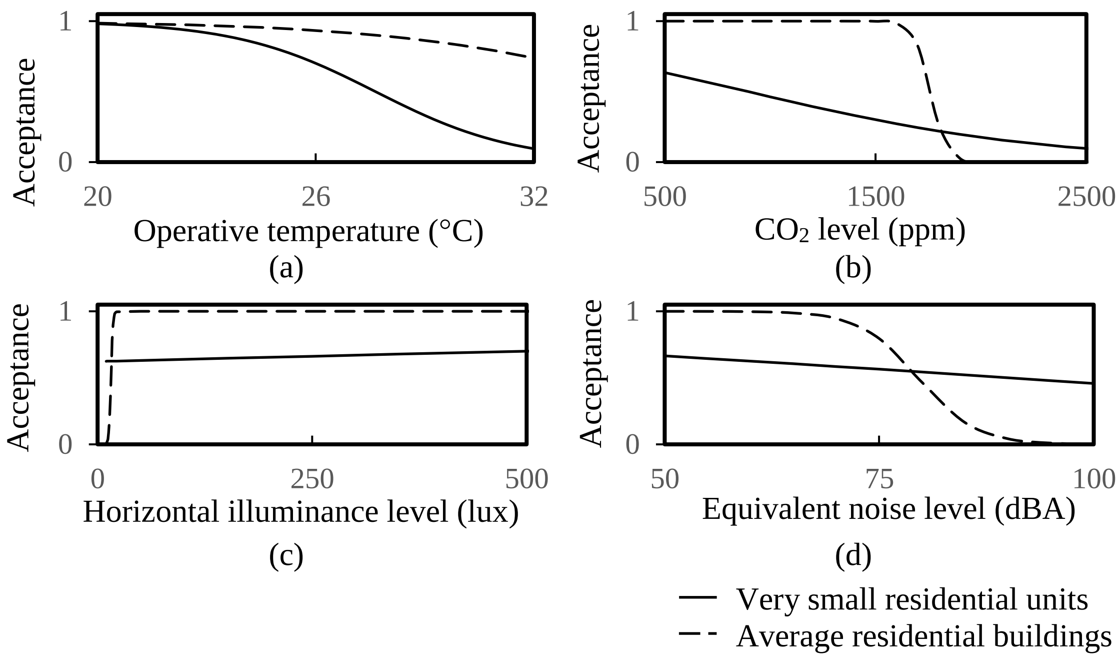


Figure 4.3 Acceptance of operative temperature, CO_2 level, horizontal illuminance level and equivalent noise level in living environments

Table 4.3 Coefficients for logistic regression equations of acceptance

i	Acceptance variable	$C_{0,i}$	$C_{1,i}$	$C_{2,i}$	$C_{3,i}$	$C_{4,i}$
0	IEQ δ_0	-0.0062	0.1710	-0.0140	0.5711	0.2695
1	Operative temperature δ_1	14.3210	-0.5181	–	–	–
2	CO_2 level δ_2	-0.0014	1.2544	–	–	–
3	Horizontal illuminance level δ_3	0.0007	0.5001	–	–	–
4	Equivalent noise level δ_4	-0.0171	1.5466	–	–	–

4.3.3. Overall indoor environmental quality acceptance

Table 4.4 exhibits the overall IEQ acceptance of occupants living in the two environments under different environmental cases j. A total of j = 2^4, i.e. 16 cases of combinations of contributors δ_i for i = 1,...,4 with binary notation for the acceptance of individual IEQ aspects (i.e. 0 for 'unsatisfied' and 1 for 'satisfied') are presented. The variations of acceptance of environmental aspects $\Delta\delta_i$ were given by Equation 4.3. Cases with zero samples in both studies were excluded from this calculation.

Table 4.4 Overall IEQ acceptance

Case j	Contributors				Very small residential units		Average residential building	
	δ_1	δ_2	δ_3	δ_4	Overall IEQ acceptance ($\delta_{0,j}$)	Sample size (n_j)	Overall IEQ acceptance ($\delta_{0,avg,j}$)	Sample size ($n_{j,avg}$)
1	0	0	0	0	0.167	6	0	1
2	0	0	0	1	0.2	5	–	0
3	0	0	1	0	0.333	3	0	1
4	0	0	1	1	0.875	8	0.5	2
5	0	1	0	0	0	1	–	0
6	0	1	0	1	–	0	0	1
7	0	1	1	0	0	1	0	2
8	0	1	1	1	1	1	0.833	6
9	1	0	0	0	–	0	0	1
10	1	0	0	1	0	2	–	0
11	1	0	1	0	1	2	–	0
12	1	0	1	1	1	2	1	2
13	1	1	0	0	0	3	–	0
14	1	1	0	1	1	1	1	7
15	1	1	1	0	0.75	4	0.857	7
16	1	1	1	1	1	13	1	95
Total						52		125

$$\Delta\delta_i = \sum_{i=1}^{4} \{\delta_0(\delta_i = 1) - \delta_0(\delta_i = 0)\} \quad – (4.3)$$

Using $\Delta\delta_i$ to indicate the expected acceptance change between the votes 0 and 1 for each environmental aspect, the results are shown in Figure 4.4. $\Delta\delta_i$ identifies the changes in overall IEQ acceptance when the vote for each environmental aspect changes from unaccepted to accepted, given that the acceptances towards other aspects remain unchanged. It can identify the difference in the effect of environmental aspects on overall IEQ acceptance by the two groups of occupants. Equation 4.3 gives $\Delta\delta_1 = 0.22$, $\Delta\delta_2 = 0.14$, $\Delta\delta_3 = 0.43$ and $\Delta\delta_4 = 0.47$ for occupants from small units, compared to $\Delta\delta_1 = 0.62$, $\Delta\delta_2 = 0.11$, $\Delta\delta_3 = 0.28$ and $\Delta\delta_4 = 0.49$ for residents of average houses. Insignificant differences in $\Delta\delta_i$ between the two environments were found (*p*-value > 0.05, *t*-test), especially for the IAQ and aural aspects (*p*-value > 0.9, *t*-test). It is noteworthy that there might be a slight difference in the thermal aspect (*p*-value = 0.2, *t*-test).

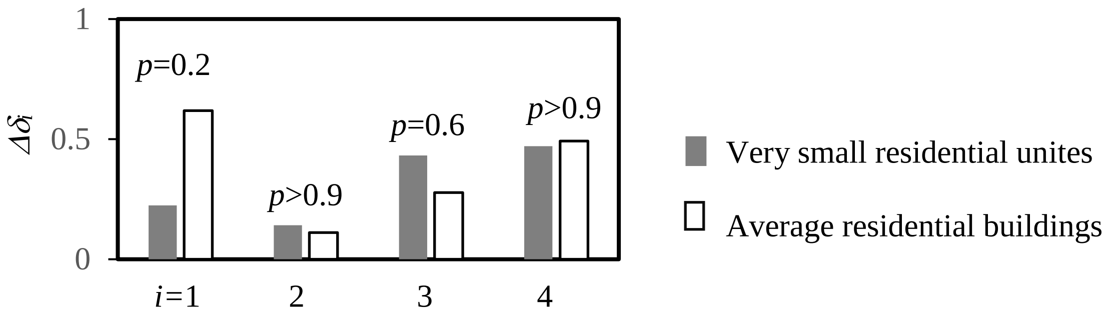


Figure 4.4 Expected acceptance change of environmental aspects

The adaptation to reality of small unit's occupants was also reflected in the environmental cases. Figure 4.5 shows the overall IEQ acceptance for all cases j when $\Delta\delta_0 = 0.1$ (unweighted) and $\Delta\delta_{0,w} = 0.04$ (weighted by sample size n_j), in which $\Delta\delta_0$ and $\Delta\delta_{0,w}$ are quantified by Equation 4.4. Weighting can adjust the statistical significance of the results. Cases with zero sample are excluded from the computation.

$$\Delta\delta_0 = \frac{\sum_j(\delta_{0,j}-\delta_{0,avg,j})}{16}; \qquad \Delta\delta_{0,w} = \frac{\sum_j(n_j\delta_{0,j}-n_{j,avg}\delta_{0,avg,j})}{\sum_j(n_j+n_{j,avg})} \qquad -(4.4)$$

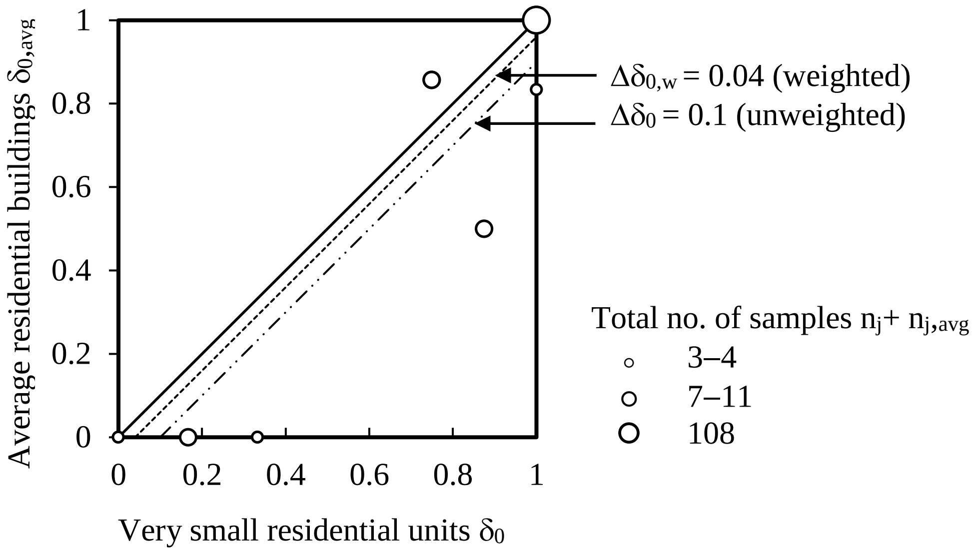


Figure 4.5 Overall IEQ acceptance

The incremental acceptance when $\Delta\delta_0 = 0.1$ over example ranges of parameters x_i and acceptances for better, average and poorer scenarios are presented in Figure 4.6. The gap between the solid line and the dotted line suggests certain degree of tolerance to level of parameter by the small unit residents. Along the two lines, the difference in level varies in different scenarios, for example, 0.04 to 0.11 PMV in poorer case. The additional acceptance level of the individual aspect gained by $\Delta\delta_0 = 0.1$ of small unit occupants is expected to be higher than that of the average house, as a higher tolerance to environmental condition is expected among small unit residents (e.g. 0.11 PMV, 220ppm, 2lux and 3.6dBA, and 0.04 PMV, 40ppm, 0.3lux and 0.4dBA).

The overall IEQ acceptance can be expressed by Equation 4.2 and regression coefficients given in Table 4.3. This regression equation is statistically significant (R = 0.80, *p*-value

< 0.05, *t*-test), gives a narrow predicted acceptance ranging from 0.47 to 0.75 for $\delta_i \in [0, 1]$, which reflects not only the hidden occupant's responses (no significant overall trend) against individual environmental parameters for CO_2, horizontal illuminance and equivalent noise levels but also the occupant adaptation to the reality of a hot environment.

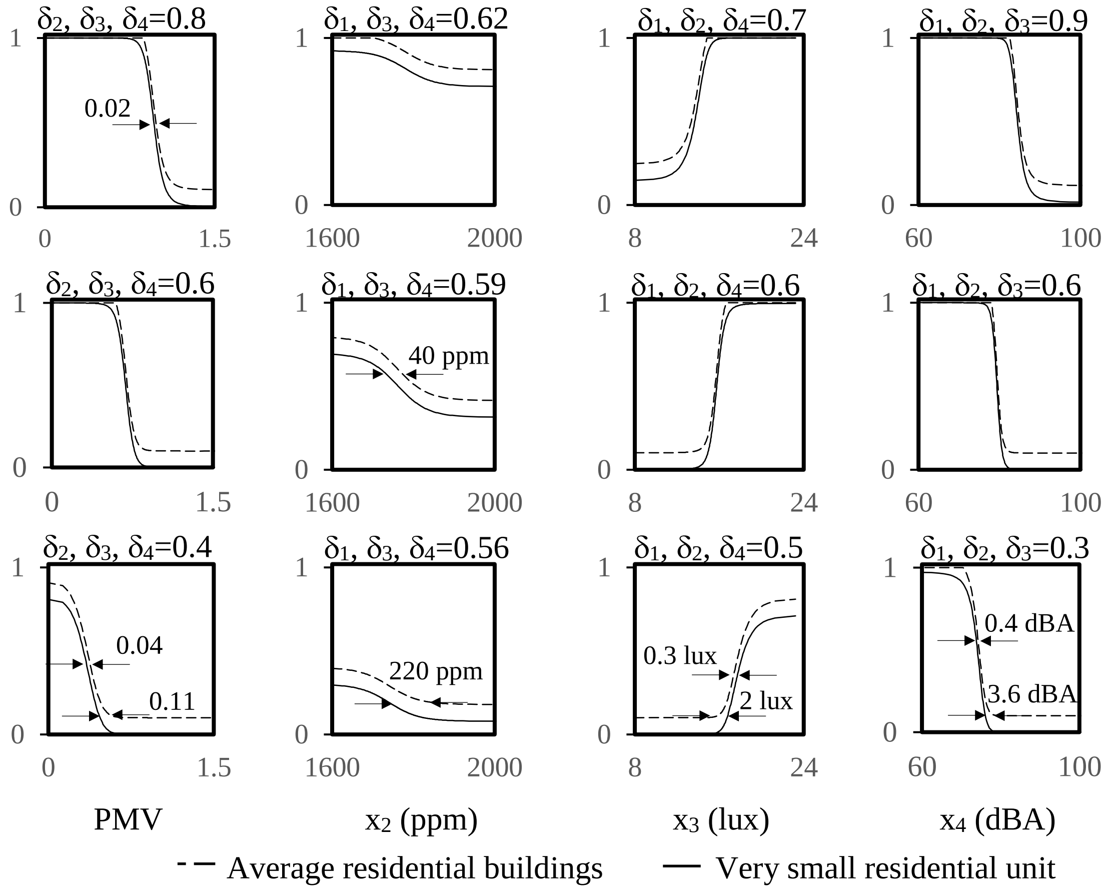


Figure 4.6 Increase in environmental acceptance over example ranges of parameters with IEQ acceptance shift $\Delta\delta_0 = 0.1$

To examine the dependence and sensitivity of the predicted overall IEQ acceptance on the variations of the IEQ aspects, example values x_2 = 800 ppm and 1800 ppm, x_3 = 10 lux and 100 lux, and x_4 = 50 dBA and 80 dBA were selected to present an observable range of indoor environmental conditions, with reference to the IEQ acceptance study in average residential buildings in Hong Kong (Lai, Mui et al., 2009). Same examples were demonstrated in previous study, therefore using these nominal conditions in this study allows simple and direct comparison. Figure 4.7 shows the dependency of IEQ acceptance given by two fixed contributors. As expected, the overall IEQ acceptance predicted for small units is very insensitive to the four IEQ parameters as compared with the average residential buildings, shown by narrow gap between the lines of different conditions. The changes in IEQ acceptance over the T_o range (20–32°C) were not significant ($\delta_0 \leq 0.051$), where changes of $\delta_0 \leq 0.5$ were reported for the average residential ones, which differs by 10-fold.

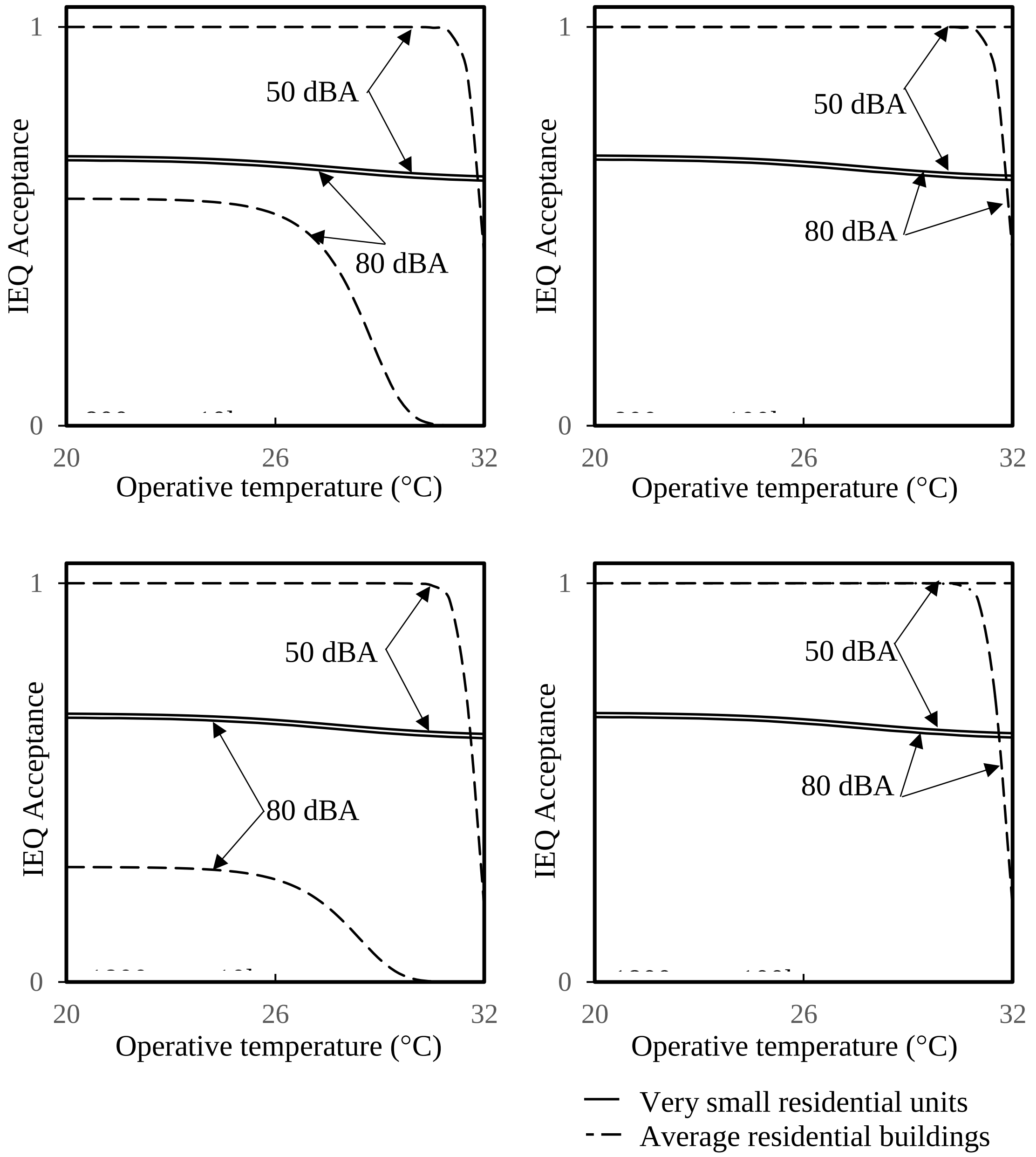


Figure 4.7 Predicted occupant’s acceptance of IEQ at various example environmental conditions

4.4. Overview of IEQ logistic regression models

Given the intricacy of IEQ factors, responses and acceptance, existing multivariate logistic regression models for IEQ acceptance prediction focus on only four major IEQ aspects, namely thermal comfort, IAQ, visual comfort and aural comfort were proposed (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). In addition, an indexing approach for IEQ assessment was proposed to correlate a set of independent parameters (including climate, building shape and window/wall noise attenuation) with the four major IEQ aspects (Catalina and Iordache, 2012). A Dwelling Environmental Quality Index was developed to reflect the indoor quality based on the air temperature, relative humidity and CO_2 level (Laskari, Karatasou et al., 2017).

Despite large database was used to develop the existing IEQ multivariate logistic regression models, which shall be statistical comprehensive enough to represent most indoor environments, in the previous sub-chapter, it was discovered that regression models are not promising to describe less favourable indoor environments with poor environmental conditions. It was reported that changing the environmental conditions do not significantly affect the IEQ acceptance when the perception of an indoor space is already adapted by occupants. Psychological effects also influence occupant's IEQ acceptance of an environment. It seems that the predicted acceptance to IEQ parameters is also influenced by the selection of logistic regression. Discrepancies between predicted IEQ and the actual results of a building performance model were reported of policy significance and the selection of regression model had significant influences on the assessment results (Majcen, Itard et al., 2013). Another study reported huge differences among predictions of seven thermal sensation models, suggesting the consequences of model selection in environmental prediction practice (Koelblen, Psikuta et al., 2017).

Furthermore, a recent study suggested additional IEQ parameters, such as privacy, cleaning and maintenance, vibration and movement, and technology could influence occupant's perception on indoor environment quality (Bae, Asojo et al., 2017). With more contributing parameters being suggested to model IEQ, developing a flexible model framework open to more parameters and their contributions to IEQ with latest available data is therefore essential (Lam, Zhao et al., 2014).

The robustness of IEQ acceptance prediction models is crucial to sustainable building development. The earlier proposed IEQ models for air-conditioned offices, classrooms and residential buildings (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012) showed limited flexibility to align with the call for the inclusion of additional IEQ parameters. Collective occupant responses expressed by multivariate logistic regressions were not promising. Indeed, the proposed regressions are yet to be confirmed for other similar environments with deviated conditions (Mui, Tsang et al., 2019).

The following sub-chapter first describes the method for developing the open probabilistic acceptance model and evaluates its prediction performance by comparing with existing IEQ logistic regression models with data available in open literature (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). The characteristics of the two models and future development of IEQ modelling are then discussed.

4.5. Development of IEQ acceptance model

Existing IEQ logistic regression model is not promising to represent occupant's responses and acceptances especially in less favourable environments. A novel open IEQ acceptance model is proposed here based on frequency distribution functions of occupant's responses towards IEQ parameters. It shall be flexible to various IEQ parameters and allow easy model updating.

The overall acceptance of an indoor environment is defined by a number of acceptances δ_i of the respective environmental parameters x_i, as shown in Equation 4.5.

$$\delta_i \sim \delta(x_i) \qquad -(4.5)$$

A total of $j = 1, 2, 3, \ldots, i^2-1, i^2$ environmental conditions can be formed as a result. The occurrence of these conditions φ_j is given by Equation 4.6, while the acceptance ρ_j with respect to each environmental condition can be expressed by Equation 4.7. The overall IEQ acceptance δ_0 is given by Equation 4.8.

$$\begin{aligned}
\varphi_j = &(1-\delta_1)(1-\delta_2)\cdots(1-\delta_{i-1})(1-\delta_i),\\
&(1-\delta_1)(1-\delta_2)\cdots(1-\delta_{i-1})(\delta_i),\\
&(1-\delta_1)(1-\delta_2)\cdots(\delta_{i-1})(1-\delta_i),\\
&\vdots\\
&(\delta_1)(\delta_2)\cdots(\delta_{i-1})(1-\delta_i),\\
&(\delta_1)(\delta_2)\cdots(\delta_{i-1})(\delta_i)
\end{aligned} \qquad -(4.6)$$

$$\rho_j = [\rho_1, \rho_2, \rho_3, \cdots, \rho_{i^2-1}, \rho_{i^2}] \qquad -(4.7)$$

$$\delta_0 = \sum_{j=1}^{i^2} \varphi_j \rho_j \qquad – (4.8)$$

The acceptance of an environmental parameter x in the range x∈[a, b] can be from acceptance (δ=1) to unacceptance (δ=0) and vice visa. Hence, the acceptance function δ of an environmental parameter is expressed in Equation 4.9.

$$\delta = \begin{cases} 1 - \int_a^x \widetilde{x} dx, & \delta(a) > \delta(b) \\ \int_a^x \widetilde{x} dx, & \delta(a) < \delta(b) \end{cases} \qquad – (4.9)$$

$\tilde{x}$ is the probability density function of normalized occupant votes for the environmental acceptance δ as expressed in the Equations 4.10–4.11, where δ = 1 indicates there are no dominant votes for acceptance or unacceptance, i.e. $\delta_s = \delta_u$ at $x = x_{su}$

$$\widetilde{x} = \frac{\delta}{\int_a^b \widetilde{\delta} dx} \qquad – (4.10)$$

$$\delta(x) = 1 - |\delta_s - \delta_u| \qquad – (4.11)$$

Percentage votes for acceptance δ_s and unacceptance δ_u with sample sizes n_s and n_u are given by the Equations 4.12–4.13, where y_s and y_u are the cumulative frequency distributions for the mass density functions of parameters $\tilde{x}_s$ and $\tilde{x}_u$ respectively. $\tilde{x}_s$ and $\tilde{x}_u$, which are the collective occupant responses to the environment, can be obtained from field survey studies.

$$\delta_s = \frac{n_s y_s}{n_s y_s + n_u y_u}; \quad \delta_u = \frac{n_u y_u}{n_s y_s + n_u y_u} \qquad – (4.12)$$

$$y_s = 1 - \int_a^x \widetilde{x}_s dx; \quad y_u = \int_a^x \widetilde{x}_u dx \qquad – (4.13)$$

Occupant responses to four indoor environmental aspects, namely thermal comfort, IAQ, noise level and illumination level, in air-conditioned offices, residential buildings and university classrooms were reviewed (Mui and Wong, 2006, Mui and Wong, 2007, Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). Table 4.5 summarizes the response data under two groups (satisfaction and dissatisfaction) in terms of four (surrogate) parameters: operative temperature x_1, CO_2 level x_2, equivalent noise level x_3 and illumination level x_4. The probability density functions of $\tilde{x}_s$ and $\tilde{x}_u$, are approximated by Equation 4.14, where μ and σ are the mean and standard deviation respectively.

$$\widetilde{x}_s = x_s(\mu_s, \sigma_s); \quad \widetilde{x}_u = x_u(\mu_u, \sigma_u) \qquad – (4.14)$$

Generally, the sample size of the dissatisfaction group was around 5–15% of that of the satisfaction group (a typical result from surveys for any built environments designed to suit the majority). However, for the CO_2 levels in classrooms and offices, the sample sizes of the dissatisfaction groups increased to 20–40%. It was noted that classroom and office occupants usually could not adjust the quantity of fresh air supply, which might be the reason for higher dissatisfaction rate.

It was also noted that although relatively large deviations were found within the response data, the average values between satisfaction and dissatisfaction groups in the survey studies were similar, e.g. the illumination level in classrooms (p = 0.8, t-test) and the CO_2 level in residential buildings (p = 0.7, t-test). For the equivalent noise level in classrooms, the means were equal between the two groups (p-value > 0.95, t-test). There was one case in which the standard deviation was larger than the mean (i.e. the illumination level in residential buildings).

Table 4.5 IEQ parameters of various indoor environments

Parameters	Satisfaction			Dissatisfaction		
	μ_s	σ_s	n_s	μ_u	σ_u	n_u
Residential (n = 125)						
Operative temperature (x_1) (°C)	27.3	2.0	113	28.8	1.9	12
CO_2 level (x_2) (ppm)	678	327	118	629	370	7
Equivalent noise level (x_3) (dBA)	66.8	5.8	113	72.5	7.7	12
Illumination level (x_4) (lux)	179	281	116	74.5	85.5	9
Classroom (n = 312)						
Operative temperature (x_1) (°C)	22.2	1.5	301	22.8	1.9	25
CO_2 level (x_2) (ppm)	1014	278	247	1190	356	79
Equivalent noise level (x_3) (dBA)	61.4	9.4	291	61.4	4.0	33
Illumination level (x_4) (lux)	369	115	294	363	124.9	29
Office (n = 293)						
Operative temperature (x_1) (°C)	21.1	1.3	264	21.4	1.2	29
CO_2 level (x_2) (ppm)	935	320	208	1147	268	85
Equivalent noise level (x_3) (dBA)	55.3	3.4	242	58.7	4.2	51
Illumination level (x_4) (lux)	674	277	246	560	384	47

Table 4.6 summarizes the occupant acceptances δ_0 under 16 environmental conditions in residential buildings, classrooms and offices regarding the four environmental parameters x_1 to x_4. Predicted acceptances made by the existing IEQ equations (i.e. the existing IEQ logistic regression model) from previous studies are presented for comparison (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). It can be seen that the predictions made were good for offices but not so for residential buildings and classrooms. It should be noted that small sample sizes (n ≤ 5) were reported in 6, 12 and 11 (out of 16) environmental conditions for residential buildings, classrooms and offices

respectively. Data in Tables 4.5 and 4.6 were adopted to evaluate the input parameters of the IEQ model proposed.

Table 4.6 IEQ acceptance from various indoor environments

Case	Acceptance of parameter				Residential (n=125)	Classroom (n=312)	Office (n=293)	Residential	Classroom	Office
j	δ_1	δ_2	δ_3	δ_4	Survey $\rho_{j,n}$			Predicted $\rho_{j,p}$		
1	0	0	0	0	0*	0.6*	**	0	0.15	0
2	0	0	0	1	0*	0.29	0	0	0.35	0
3	0	0	1	0	**	0*	0*	0	0.57	0
4	0	0	1	1	0.5*	0.57	0	0.50	0.80	0
5	0	1	0	0	**	**	0*	0	0.32	0
6	0	1	0	1	0*	0.67*	0*	0	0.58	0
7	0	1	1	0	0*	0.75*	0	0	0.78	0
8	0	1	1	1	0.833	0.94	0.15	0.83	0.91	0.15
9	1	0	0	0	0*	0*	0*	0	0.37	0
10	1	0	0	1	**	0.67*	0.2	0.55	0.63	0
11	1	0	1	0	**	0.4*	0	1	0.81	0.02
12	1	0	1	1	1*	1	0.38	1	0.93	0.38
13	1	1	0	0	**	0.6*	0*	0	0.61	0.02
14	1	1	0	1	0.857	0.57*	0.41	0.86	0.82	0.41
15	1	1	1	0	1	0.83*	0.67	1	0.92	0.67
16	1	1	1	1	1	0.95	0.99	1	0.97	0.99

Remark: Sample size: *≤ 5, **0.

4.5.1. Acceptance of environmental parameters

Figure 4.8 plots the voting percentages for acceptance δ_s and unacceptance δ_u of the four parameters x_1 to x_4 in residential buildings, classrooms and offices. T_o range is 19−32°C, CO_2 level range is 400−2000ppm, equivalent noise level range is 50−85dBA and illumination level range is 10−1500lux. Responses to the operative temperature and equivalent noise level are sensitive to different premises categories and they are clearly distinguished in Figures (a) and (c). As illustrated in Figure (b), responses to the CO_2 level are overlapping among the three premises categories. Figure (d) shows that the illumination level in classrooms is usually around 500lux, while the range of illumination levels is wider in residential buildings and offices.

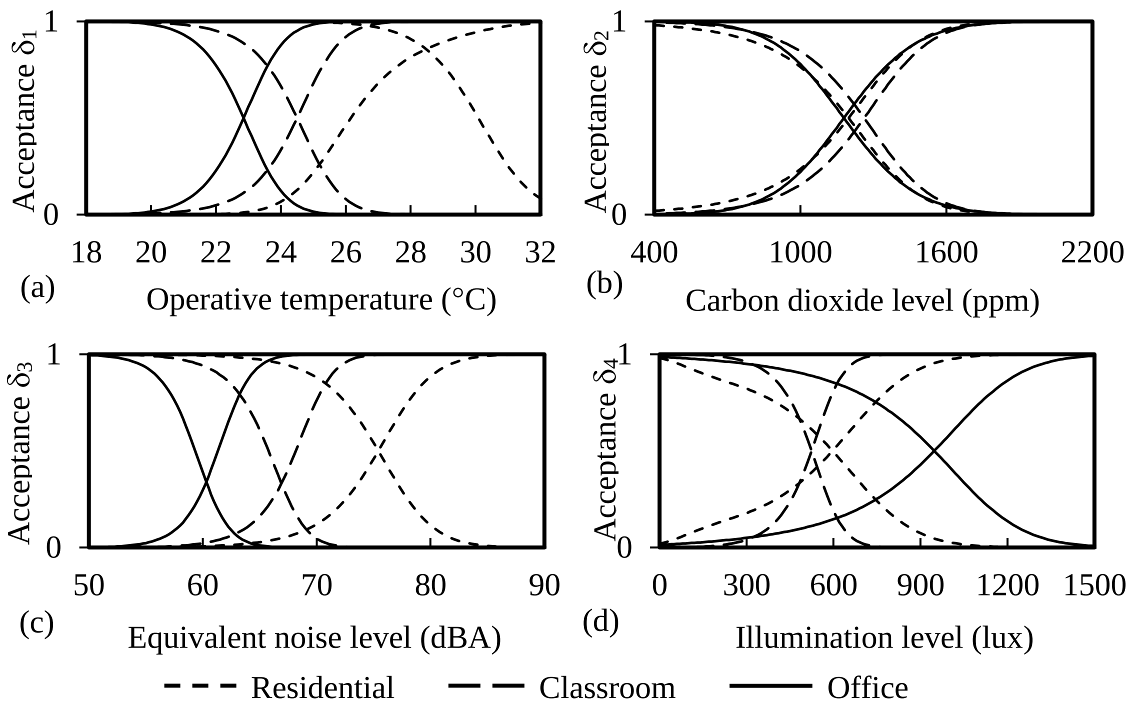


Figure 4.8 Percentage votes for acceptance ($\delta_i = 1$) and unacceptance ($\delta_i = 0$) with (a) operative temperature; (b) CO_2 levels; (c) equivalent noise levels; and (d) illumination

Determined by δ_s and δ_u, the probability density functions of normalized votes $\tilde{x}$ for x_1–x_4 are shown in Figure 4.9(i). Results show significant mean differences of $\tilde{x}$ between functions ($p \leq 0.01$, t-test), except for CO_2 levels (Figure 4.9(b)) and illumination levels between residential buildings and classrooms (p-value > 0.01, t-test). Figures 4.9(ii)–(iv) suggest that reasonable normal approximations can be made with $\tilde{x} \sim x(\mu,\sigma)$.

Parametric distributions, presented in Table 4.7, were adopted as the model parameters x_1 to x_4. The goodness of fit was examined using the cumulative frequency distributions δ for $\tilde{x}$ and $x(\mu,\sigma)$ shown in Figures 4.10(i) and 4.10(ii) respectively. The maximum absolute errors ε_M, determined by Equation 4.15, were 0.01–0.08.

$$\varepsilon_M = max\left(\left|\int_x x(\mu,\sigma)dx - \int_x \tilde{x}dx\right|\right); \quad \forall x \epsilon [a,b] \qquad \text{– (4.15)}$$

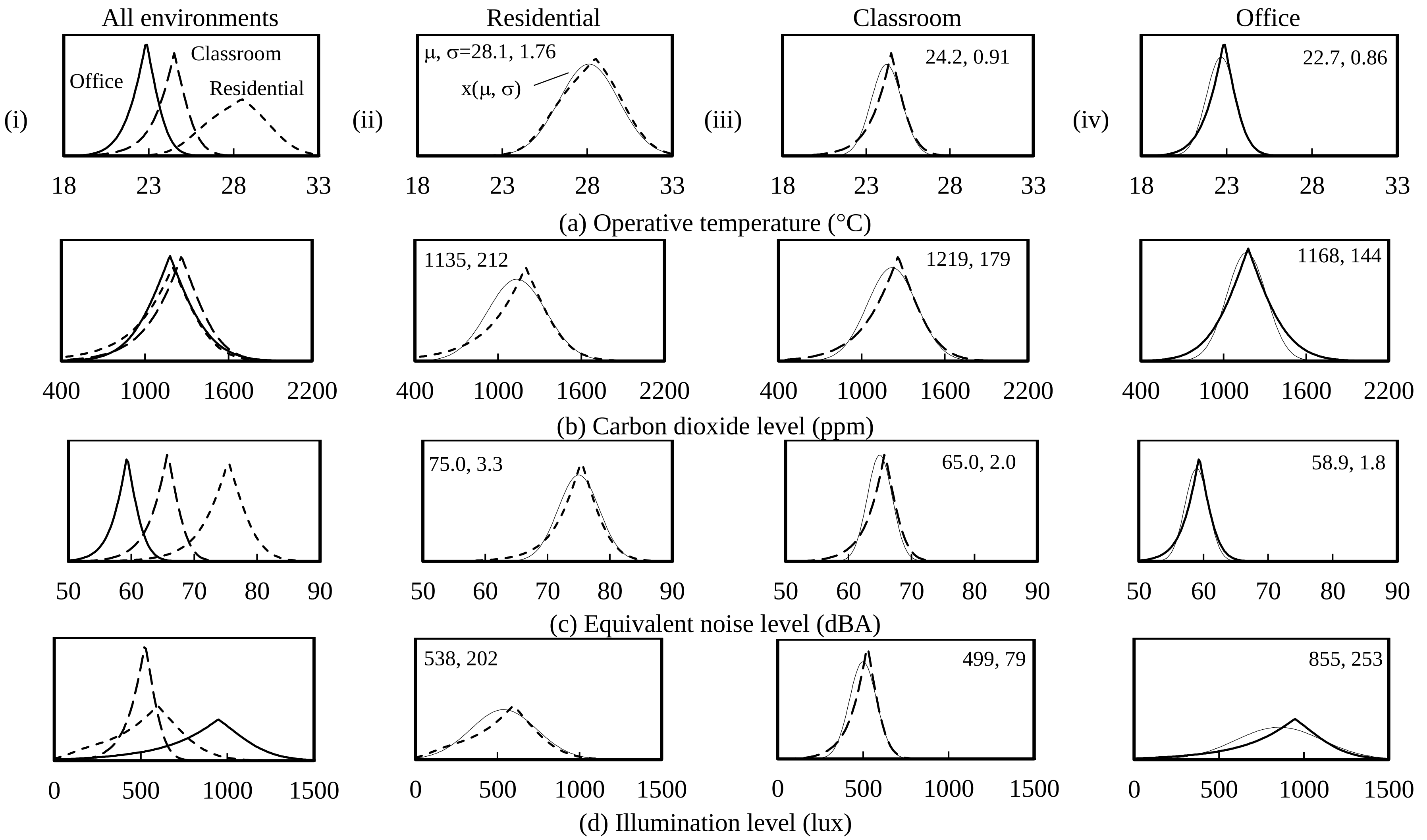


Figure 4.9(i) Probability density functions of normalized votes $\tilde{x}$ approximated with $x(\mu,\sigma)$; (ii)–(iv) Reasonable normal approximations made with $\tilde{x} \sim x(\mu,\sigma)$; for (a) operative temperature; (b) CO_2 levels; (c) equivalent noise levels; and (d) illumination

Figures 4.10(i) and 4.10(ii) present zero acceptances at/ beyond the measurement boundaries of dissatisfaction as no occupant responses were previously recorded in typical built environments under extreme environmental conditions. These acceptances can be interpreted as the environmental acceptances from both the occupants and the building designers. Occupant acceptance predictions for environment parameters δ made in the previous studies are shown in Figure 4.10(iii) for comparison (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012)

In Figure 4.10(a)(iii), the thermal comfort acceptance calculated using Fanger's PMV is plotted against the operative temperature. A line of case maximum values is shown to indicate the thermal acceptance through clothing adjustment. At 31.4°C, the maximum indoor operative temperature recorded, the minimum predicted acceptance was 0.54. Similar results were observed for IAQ and aural environment. At the recorded maximum CO_2 levels of 1627ppm and 1883ppm, the predicted acceptance values for classrooms and offices were 0.54 and 0.51 respectively; for the entire measurement range of CO_2 levels up to 1499ppm in residential buildings, the predicted acceptance value was 1. At the maximum equivalent noise levels of 78dBA, 67dBA and 68dBA, the predicted acceptance values for residential buildings, classrooms and offices were 0.61, 0.88 and 0.62 respectively. Regarding the visual environment, at the measured minimum illumination level of 189lux, the minimum predicted acceptance for offices was 0.51; and for the entire illumination range recorded in residential buildings and classrooms, the predicted acceptance values were 1 and 0.90–0.92 respectively. However, a rapid (almost a step) change in acceptance from 1 to 0 was found at around 10lux in residential buildings.

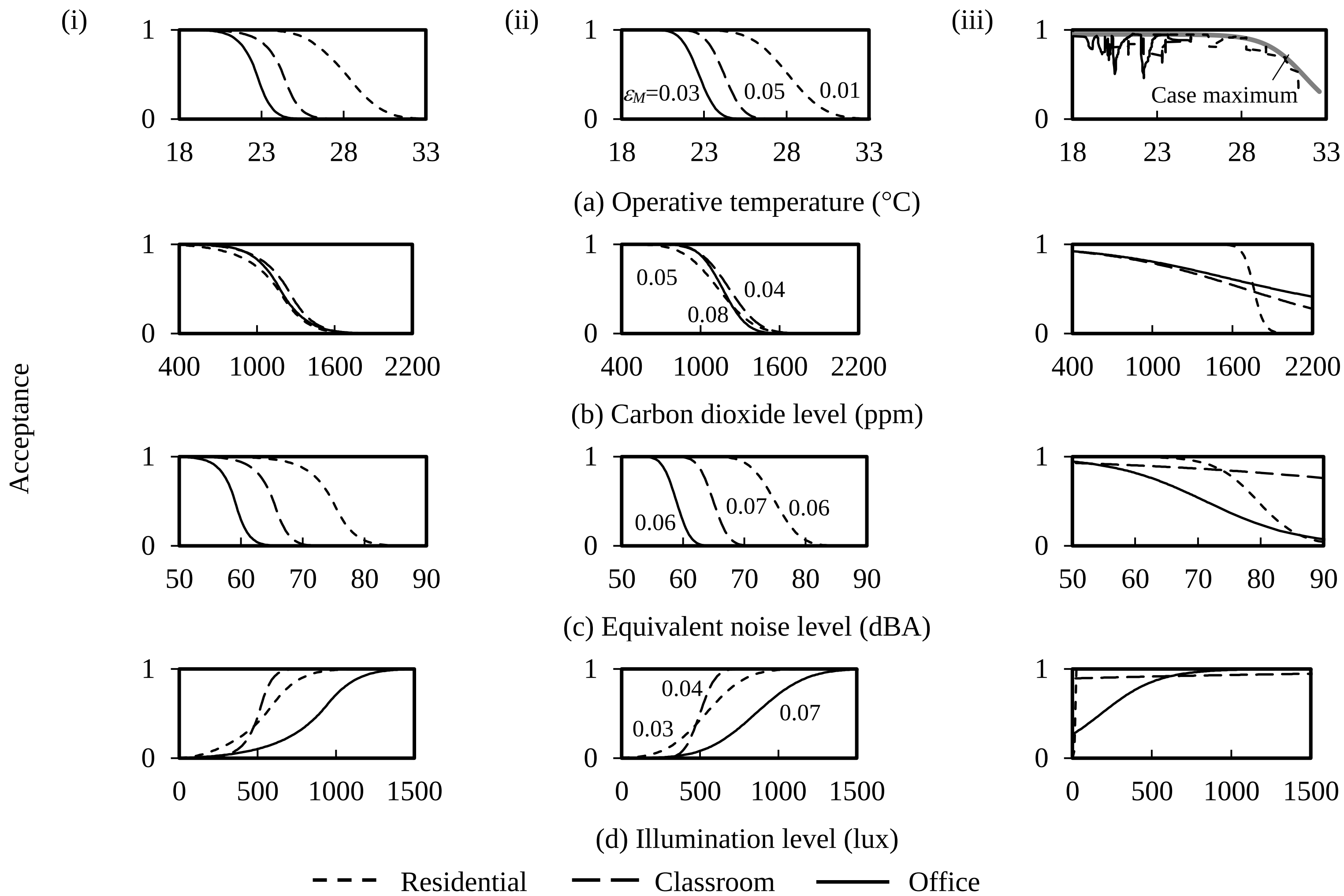


Figure 4.10(i) Cumulative frequency distributions δ for x̃; (ii) Cumulative frequency distributions δ for x(μ,σ); (iii) Predicted occupant acceptance δ; for (a) operative temperature; (b) CO_2 levels; (c) equivalent noise levels; and (d) illumination

Within the measurement range, the proposed model would result in zero acceptances at/ beyond the boundaries, while prediction from previous studies most of the time would give an acceptance $\neq 0$ at the measurement boundaries. The acceptance results from proposed model are distinguished from those obtained from the earlier studies (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). It can be explained with reason that the built environmental conditions were constrained by some design norms, the predicted acceptance was comparatively higher in the measurement parameter range than in the observable parameter range. As the collective results from a field survey are not only directly from the respondents but also indirectly from those who have contributed to the environmental settings (i.e. building designers and operators), the fundamental settings of a field survey should be taken as constraints for occupant responses. Therefore, when logistic regression model was used in extreme environment as demonstrated previously, occupant's responses did not follow the trend described in model developed using average environmental condition, as the measurement parameter range this time was beyond the boundary in normal environments.

Moreover, acceptance of environmental parameters is model dependent. In a multivariate logistic regression model, the higher prediction may be interpreted as a bias towards the acceptable environment, whereas in a frequency distribution model, the higher prediction may be interpreted as a bias towards the comfortable environment.

4.5.2. Acceptance of indoor environment

IEQ acceptances ρ_j under environmental conditions j for residential buildings, classrooms and offices are shown above in Table 4.6. For those conditions without any survey data, predictions from the previous studies were adopted, demonstrated in Table 4.7.

Table 4.7 Model parameters

Parameter	Symbol	Residential		Classroom		Office	
		μ	σ	μ	σ	μ	σ
Operative temperature (°C)	x_1	28.1	1.76	24.2	0.91	22.7	0.86
CO_2 level (ppm)	x_2	1135	212	1219	179	1168	144
Equivalent noise level (dBA)	x_3	75.0	3.3	65.0	2.0	58.9	1.8
Illumination level (lux)	x_4	538	202	499	79	855	253
Probability of environmental acceptance ρ_j	ρ_1	0		0.60		0^{**}	
	ρ_2	0		0.29		0	
	ρ_3	0^{**}		0.57		0	
	ρ_4	0.5		0.57		0	
	ρ_5	0^{**}		0.32^{**}		0	
	ρ_6	0		0.67		0	
	ρ_7	0		0.75		0	
	ρ_8	0.83		0.94		0.15	
	ρ_9	0		0.37		0	
	ρ_{10}	0.55^{**}		0.67		0.2	
	ρ_{11}	1^{**}		0.40		0	
	ρ_{12}	1		1		0.38	
	ρ_{13}	0^{**}		0.60		0	
	ρ_{14}	0.86		0.57		0.41	
	ρ_{15}	1		0.83		0.67	
	ρ_{16}	1		0.95		0.99	

ρ_j–acceptance scenarios according to Table 4.6.

Remark: sample size: $^{**}0$.

Figure 4.11(a) graphs the predictions against the measurements for this proposed model. Figure 4.11(b) plots the results obtained from the existing IEQ equations for comparison (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). As the predicted values from this and the previous studies were found to be highly correlated with a slope of 1 and a constant of 0 (p-value < 0.0001, t-test), the model proposed (i.e. Equation 4.8) should statistically give the same overall IEQ acceptance as the existing IEQ logistic regression model.

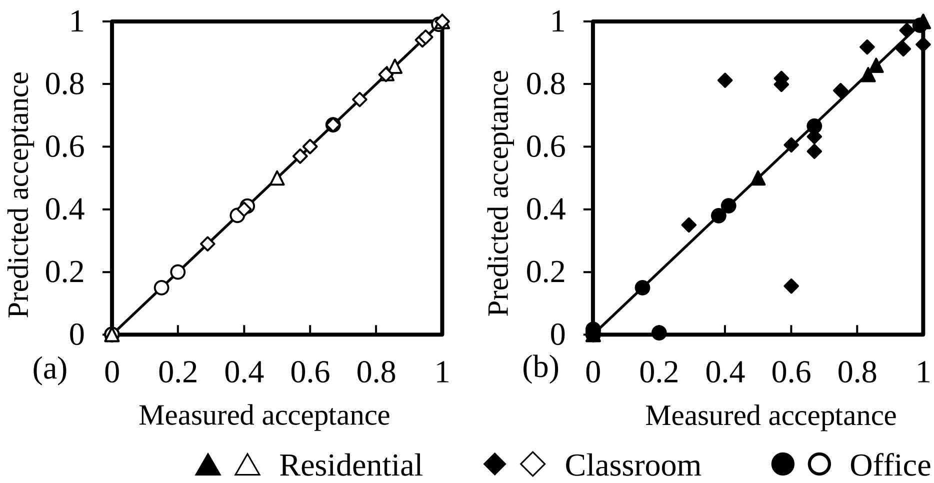


Figure 4.11 Occupant acceptances of environmental conditions ρ_j (a) The proposed model (white); and (b) IEQ equations (black)

4.6. Model predictions and performance

Figure 4.12 illustrates the predicted IEQ acceptances by the proposed model for residential buildings, classrooms and offices under typical indoor environmental conditions: operative temperature x_1 = 20–32°C, CO_2 level x_2 = 800–1800ppm, equivalent noise level x_3 = 50–75dBA and illumination level x_4 = 10–500lux, alongside with acceptances by the existing IEQ equations (Wong, Mui et al., 2008, Lai, Mui et al., 2009, Lee, Mui et al., 2012). According to Figure 4.12(a), variations in acceptance are small over a wide range of environmental conditions in residential buildings, except for a sharp drop predicted by the IEQ equations at around 30°C in a dark environment (i.e. x_4 = 10lux).

Existing IEQ equations work very well for offices. Under typical design conditions of 24°C, 800ppm, 50dBA and 500lux, the predicted acceptance is 0.93. Besides, variations in acceptance are reasonable and no sharp turns or flat variations are observed in Figure 4.12(b). Although the model proposed gives similar prediction patterns, it is less sensitive to parameter changes. However, data available are insufficient to judge the prediction accuracy of the proposed model or the IEQ equations. Overall, the proposed model presents notable resolutions for the environmental differences.

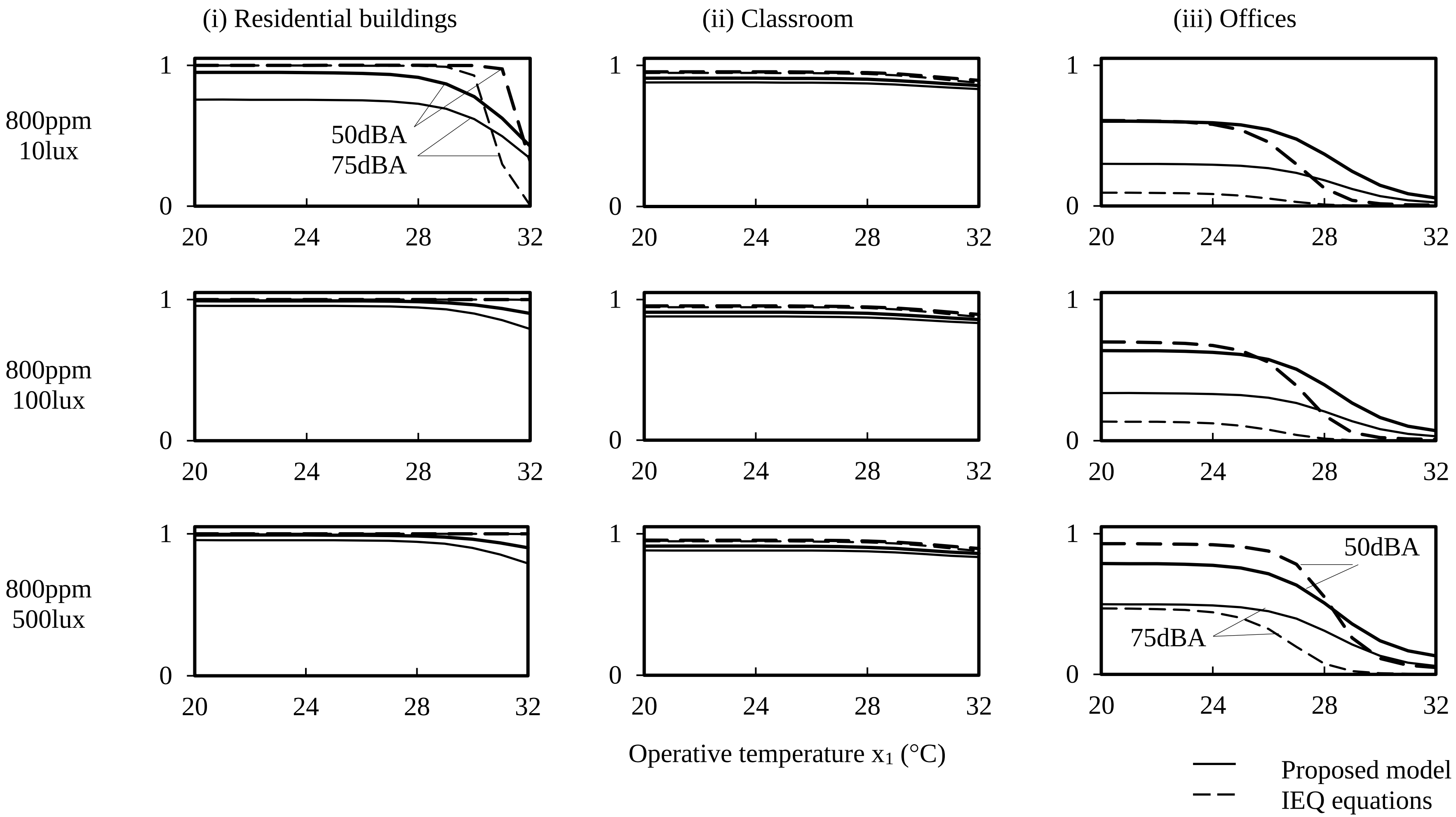


Figure 4.12(a) Predicted IEQ acceptances for (i) Residential buildings; (ii) Classrooms; (iii) Offices with (a) CO_2 level = 800ppm

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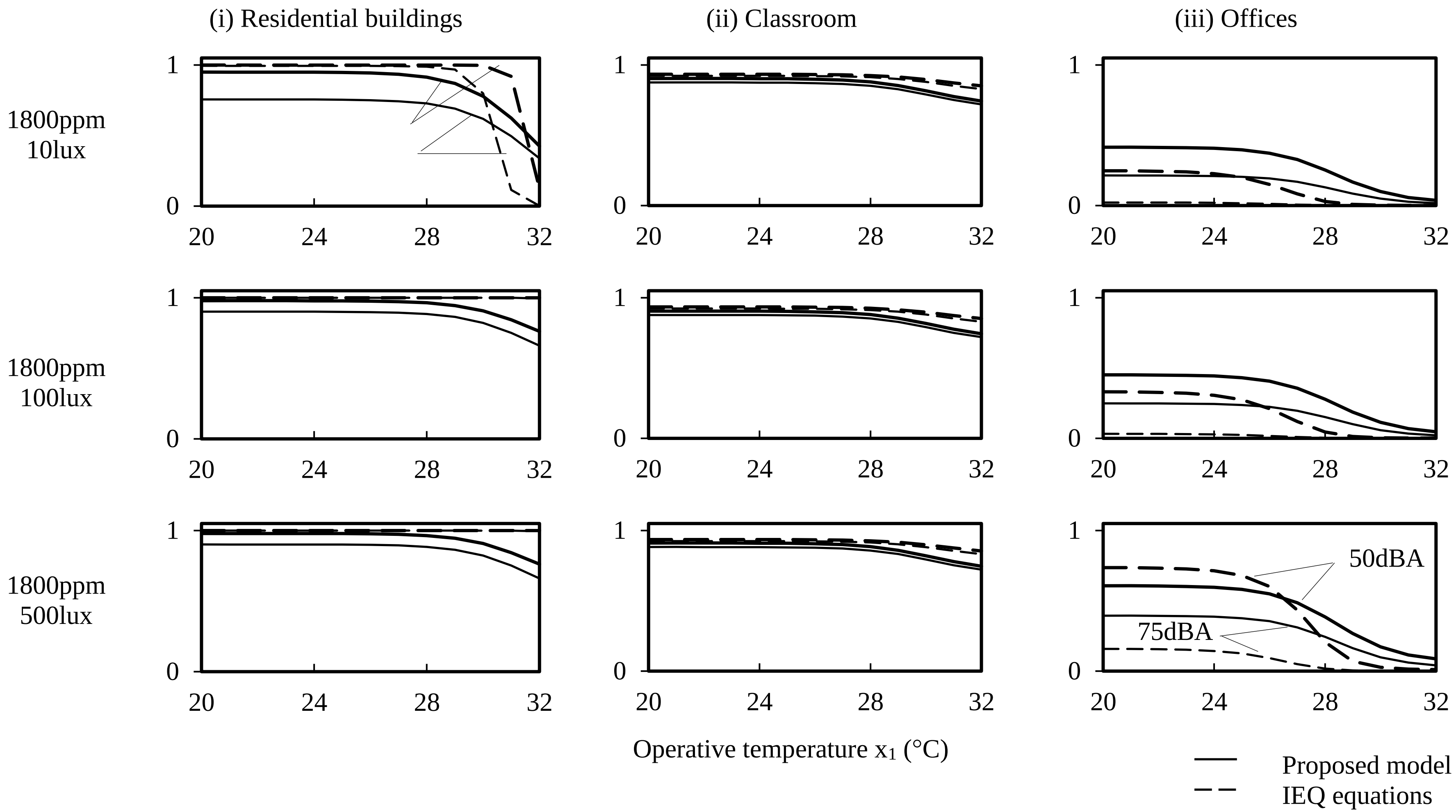


Figure 4.12(b) Predicted IEQ acceptances for (i) Residential buildings; (ii) Classrooms; (iii) Offices with (b) CO_2 level = 1800ppm

4.7. Summary

Population growth and urbanization have promoted the development of small houses and high-rise multi-unit residential buildings. The fast-changing housing situation of the world encourages the enhancement of understandings on IEQ in residential environments. In this chapter, field surveys are conducted in very small residential units to investigate the IEQ responses from occupants. Through the changes in thermal, IAQ, visual and aural environmental parameters, it is demonstrated that the overall IEQ acceptance of occupants in small units is different from those residing in average residential buildings. Small unit residents are more sensitive to warmth and operative temperature change as compared to occupants of average houses. A small variation in thermal acceptance suggested that the small unit residents have developed certain degree of tolerance to hot conditions. The adaptation to the reality of a hot environment is also reflected in the overall IEQ acceptance. It is believed that they have already developed tolerance and adaptation to an unchangeable reality, changing environmental conditions does not necessarily alter their acceptance to individual IEQ aspects and overall IEQ.

This survey reveals the effects of perception, adaption and tolerance on subjective IEQ responses towards perceived environment, despite the environmental conditions of small units and average houses were actually similar. Compared to using objective criteria to assess an environment, subjective evaluation, in certain circumstance, may be more reliable in reflecting occupant's feelings and comfort inside the premises, which are the prime interests of building operators. It is therefore crucial to incorporate subjective elements into IEQ prediction models. IEQ responses collected in field can improve model prediction accuracy by considering also the user's point of view, instead of just from the building professional's perspective.

Multivariate logistic regression IEQ prediction models have been found to be not accurate in describing less favourable indoor environments with poor environmental conditions. Within the measurement range, prediction by IEQ equations most of the time would give an acceptance $\neq 0$ at the measurement boundaries. Given that built environmental conditions usually follow some design norms, the predicted acceptance by IEQ equations are comparatively higher in the measurement parameter range than in the observable parameter range. As the collective results from a field survey reflect not only the comfort responses from occupants, but also from those who have contributed to the environmental settings (i.e. building designers and operators), the fundamental settings of a field survey should be taken as constraints for occupant responses.

In addition, acceptance of environmental parameters is model dependent. The higher acceptance prediction by multivariate logistic regression model may be interpreted as a bias towards the acceptable environment, whereas in a frequency distribution model, the higher prediction may be interpreted as a bias towards the comfortable environment.

In view of the above reasons, this chapter also proposes an open acceptance model that uses frequency distribution functions of occupant responses towards IEQ parameters to assess IEQ. The proposed model gives zero acceptances at/ beyond the boundaries, which can be interpreted as the environmental acceptances by both the occupants and the building designers.

Acceptances of individual IEQ parameters and of the overall IEQ predicted by this model are tested against those predicted by an existing IEQ logistic regression model (i.e. the existing IEQ equations). While the individual acceptance results are compatible, the overall acceptance values predicted by both models are statistically the same.

Tested compatible with the existing IEQ equations for environmental acceptance predictions in residential buildings, classrooms and offices, the proposed model is considered to be valid. The overall acceptance values predicted by both models are statistically the same. The proposed model is not only flexible enough to encapsulate a diverse range of descriptive model parameters but also feasible for openly available IEQ acceptance data. Simple modelling method offers the flexibility to add data incrementally to allow easy model updating when a new set of observations arrives, this model can be a solution to the existing problems and limitations encountered in IEQ modelling.

Chapter 5. Development of Bayesian updating protocols

5.1. Introduction

In previous chapters, the subjective-objective nature of thermal comfort and overall IEQ has been greatly explored. Objective-criteria assessment approach provides a standardized and objective way to evaluate building performance potential, it however lacks the elements of occupant's influence and subjective perceptions, therefore even if comfort requirements are met, occupants may still feel unsatisfied (Burge, 2004). On the other hand, subjective-objective approach relates environmental quantities with occupant's responses, which reflects occupant's state of mind and preference for environmental conditions. Occupant's responses to perceived environment, however, may change over time with adaption, tolerance and lived experience.

In addition, the interconnection and prioritization of IEQ factors on overall IEQ have been some of the greatest obstacles for developing a generalized and comprehensive subjective-objective IEQ acceptance prediction model. These relationships between factors are often task and/ or occupant-specific, therefore the characteristics of database used for model development significantly affect the quality and applicability of IEQ models.

Conducting subjective survey can therefore identify these uncertainties and discrepancies between model predictions and actual responses, and incorporating the new subjective assessment results into existing prediction models helps improve the model accuracy by updating the relationship between environmental parameters and occupant satisfaction in prediction model.

To improve the prediction accuracy of existing model in a particular setting, this chapter proposes the Bayesian updating protocols to systematically update current subjective-objective beliefs. It is demonstrated with IEQ regression equation and Fanger's PMV/PPD model. With openly available field data in literature, Bayesian approach can allow the incorporation of statistical significance of field settings and occupant's perceptions into existing model, therefore reflecting occupant's subjective responses that are distinct from purely physiological responses to environments obtained in experiments, or deviate from prior belief of subjective-objective relationship established previously. The results shall provide an analytical solution to building owners and operators regarding the choice of IEQ parameters in environmental design and management. It is believed that with limited resources, this Bayesian approach for model updating can be a solution to improve thermal comfort and overall IEQ prediction accuracy.

5.2. Bayesian estimates and parameter

Bayes' theorem, which relates the conditional and marginal probabilities of stochastic events A and B (where B has a non-vanishing probability), asserts that the probability of event A given event B depends not only on the relation between events A and B but also on the marginal probability of occurrence of each event. This theory can be applied to a sample size not large enough for decision-making purposes, yet relevant enough for statistical analysis. Its general formulation and various applications are available in literature (Vick, 2002).

The proposed approach predicts collective acceptance of an environmental condition using the readily available information (event A) and the new measurements from an indoor environment (event B) (Wong, Mui et al., 2014). If a measured acceptance value ρ_n is significantly different from a prior belief of the acceptance ρ_0, then $|\rho_0 - \rho_n| > \varepsilon$, where ε is the cut-off value of an acceptable error. Given a measured acceptance value ρ of an environment with attributes j approximated by a normal distribution, $\rho_{j,n} \sim N(\mu,\sigma^2)$, the posterior estimate of the acceptance $\rho_{j,1} \sim N(\mu_1,\sigma_1^2)$ is expressed by the following Bayesian rules (Lee, 2004), shown in Equations 5.1–5.2, where $\rho_{j,0} \sim N(\mu_0,\sigma_0^2)$ is the prior estimate of the acceptance towards environmental attributes j, P is the probability, μ and σ^2 are the mean and variance of the normal distribution function, and μ, μ_0, and μ_1 are the best estimates of the measured, prior and posterior acceptance values respectively.

$$P\left(\rho_{j,1} \mid \rho_{j,n}\right) = P(\rho_{j,0})P(\rho_{j,n} \mid \rho_{j,0}) \qquad -(5.1)$$

$$\sigma^2 = \frac{1}{\sigma_0{}^{-2} + \sigma^{-2}}; \quad \mu_1 = \frac{\mu_0 \sigma_0{}^{-2}}{\sigma_0{}^{-2} + \sigma^{-2}} + \frac{\mu \sigma^{-2}}{\sigma_0{}^{-2} + \sigma^{-2}} \qquad -(5.2)$$

In these rules, the weightings are proportional to their respective variances, and the posterior mean is a weighted average of the prior mean and the measured value given. This posterior mean can be characterized in Equation 5.3 by the ratio of standard deviations and expressed as a parameter β^2.

$$\beta^2 = \frac{\sigma^2}{\sigma_0{}^2} \qquad -(5.3)$$

Suppose repeated measurements will deliver the measured acceptance ρ_n and denote: $X = \frac{\sigma_0{}^{-2}}{\sigma_0{}^{-2} + \sigma^{-2}} = \frac{\beta^2}{1+\beta^2}$ and $Y = \frac{\mu \sigma^{-2}}{\sigma_0{}^{-2} + \sigma^{-2}} = \frac{\mu}{1+\beta^2}$ then the posterior estimates μ_1, μ_2, …, μ_n are given by Equation 5.4.

$$\begin{aligned}
\mu_1 &= \mu_0 X + Y; \\
\mu_2 &= \mu_0 X^2 + XY + Y; \\
&\vdots \\
\mu_N &= \mu_0 X^N + Y\left(X^{N-1} + X^{N-2} + \cdots + X + 1\right) \\
&= \mu_0 X^N + \frac{Y\left(1 - X^N\right)}{1 - X}
\end{aligned} \qquad -(5.4)$$

In Equation 5.4, $\mu_N \rightarrow \mu$ when $N \rightarrow \infty$. Taking N as a finite number of the repeated observations such that the N-th estimate shows no significant difference from the measured acceptance, i.e. $|\mu_N - \mu| \leq \varepsilon$, then β^2 can be determined by Equations 5.5–5.6. Constant c_r is the ratio of the acceptable error to the difference between the prior percentage dissatisfied (PD) value μ_0 and the measured PD value μ.

$$
\begin{aligned}
\mu_N &= \mu_0 X^N + \frac{Y\left(1 - X^N\right)}{1 - X} \\
&= \mu_0 \left(\frac{\beta^2}{1+\beta^2}\right)^N + \frac{\mu}{1+\beta^2} \times \frac{1 - \left(\frac{\beta^2}{1+\beta^2}\right)^N}{1 - \left(\frac{\beta^2}{1+\beta^2}\right)} \\
&= \mu + \varepsilon
\end{aligned}
\qquad -(5.5)
$$

$$
\beta^2 = \frac{c_r{}^{\frac{1}{n}}}{1 - c_r{}^{\frac{1}{n}}}; \quad c_r = \frac{\varepsilon}{|\mu_0 - \mu|} \qquad -(5.6)
$$

With a sample size $n < N$ and β^2 as given in Equation 5.6, the Bayesian estimate for the PD value μ' is expressed by Equation 5.7.

$$
\mu' = \mu_0 X^m + \frac{Y\left(1 - X^m\right)}{1 - X}; \quad X = \frac{\beta^2}{1+\beta^2}; \quad Y = \frac{\mu}{1+\beta^2} \qquad -(5.7)
$$

5.3. Bayesian updating for overall IEQ model

Bayesian updating framework for IEQ model aims at updating the existing subjective-objective relationship of model in order to improve the accuracy and model applicability. The flow of Bayesian approach is presented in Figure 5.1 for easy understanding.

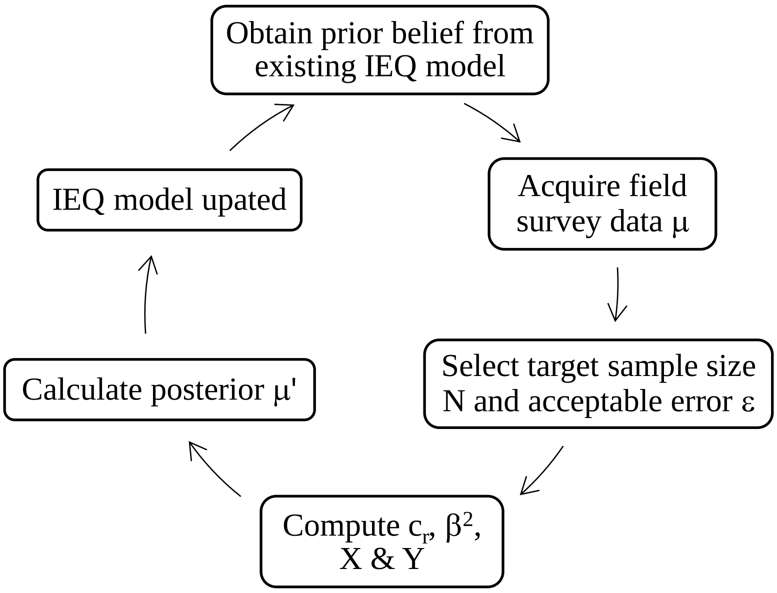


Figure 5.1 Schematic diagram of Bayesian updating approach on IEQ acceptance model

5.3.1. Bayesian updating procedures and results

In order to present this Bayesian approach for IEQ model updating, target sample sizes N of 5 (choice A) and 10 (choice B), and an acceptable error ε of 0.01 are chosen as example managerial decisions. Two prior beliefs are adopted. First, a uniform prior $\rho_{j,0}$ which environment contributors weigh equally in the overall IEQ acceptance (i.e. thermal comfort, IAQ, visual and aural condition affect occupant's IEQ acceptance in equal manner) is assumed to represent a situation when we do not have any previous IEQ understandings of a new environment. Second, the predicted probability of acceptance of 16 environmental cases generated by logistic regression model for average residential buildings by Lai, Mui et al. (2009) are also adopted. This prior belief represents an example where some degree of understandings of a certain environment are known, and newly acquired information are available to improve the accuracy of existing model.

Table 5.1 shows the prior IEQ acceptance under different cases of environmental conditions (total number of cases $j = 2^4 = 16$ cases). IEQ contributors with binary notation 0 = unsatisfied and 1 = satisfied for thermal comfort, IAQ, visual and aural acceptance are presented. In average residential buildings, most of the occupants voted for case j = 16, which indicated that they were mostly satisfied with the environment conditions. It is assumed that people have more control over the living environments and therefore they adjust to those that fit them. It is also noteworthy that only 11 out of 16 cases were recorded with votes, and only 4 cases with $n \geq 5$. In regression analysis, survey data with small sample size are not included, making the model less sensitive to poor conditions. On the other hand, for residents of very small flat units, substantial of them voted for case j = 1 to 4, indicating that the majority of them were not satisfied with the environmental conditions. Only 2 out of 16 cases did not record any vote, showing that the occupant's opinions towards the environmental conditions were more diverse.

Table 5.1 Prior IEQ acceptance ($\rho_{j,0}$) in case j = 1, 2, 3, …, 16 in (a): uniform prior acceptance; (b): multivariate logistic regression model (Lai, Mui et al., 2009); (c) measured environmental acceptance $\rho_{j,n}$ in very small flat units

Case	IEQ Contributor				(a) Uniform Prior	(b) Regression model		(c) Very small flat units	
j	Thermal	IAQ	Visual	Aural	$\rho_{j,0}$	n	$\rho_{j,0}$	n	$\rho_{j,n}$
1	0	0	0	0	0	1	2×10^{-15}	6	0.167
2	0	0	0	1	0.25	0	8×10^{-6}	5	0.2
3	0	0	1	0	0.25	1	3×10^{-10}	3	0.333
4	0	0	1	1	0.5	2	0.5	8	0.875
5	0	1	0	0	0.25	0	1×10^{-14}	1	0
6	0	1	0	1	0.5	1	4×10^{-5}	0	–
7	0	1	1	0	0.5	2	2×10^{-9}	1	0
8	0	1	1	1	0.75	6	0.83	1	1
9	1	0	0	0	0.25	1	9×10^{-6}	0	–
10	1	0	0	1	0.5	0	0.9999	2	0
11	1	0	1	0	0.5	0	0.55	2	1
12	1	0	1	1	0.75	2	1	2	1
13	1	1	0	0	0.5	0	5×10^{-5}	3	0
14	1	1	0	1	0.75	7	0.9999	1	1
15	1	1	1	0	0.75	7	0.86	4	0.75
16	1	1	1	1	1	95	1	13	1
Total					–	125	–	52	–

Bayesian approach has the power to evaluate the statistical significance of field measurement data based on its sample size and relate it to existing model with a choice of target sample size N and acceptable error ε (Wong, Mui et al., 2014). Different target sample size N would result in different posterior probability ρ_j'.

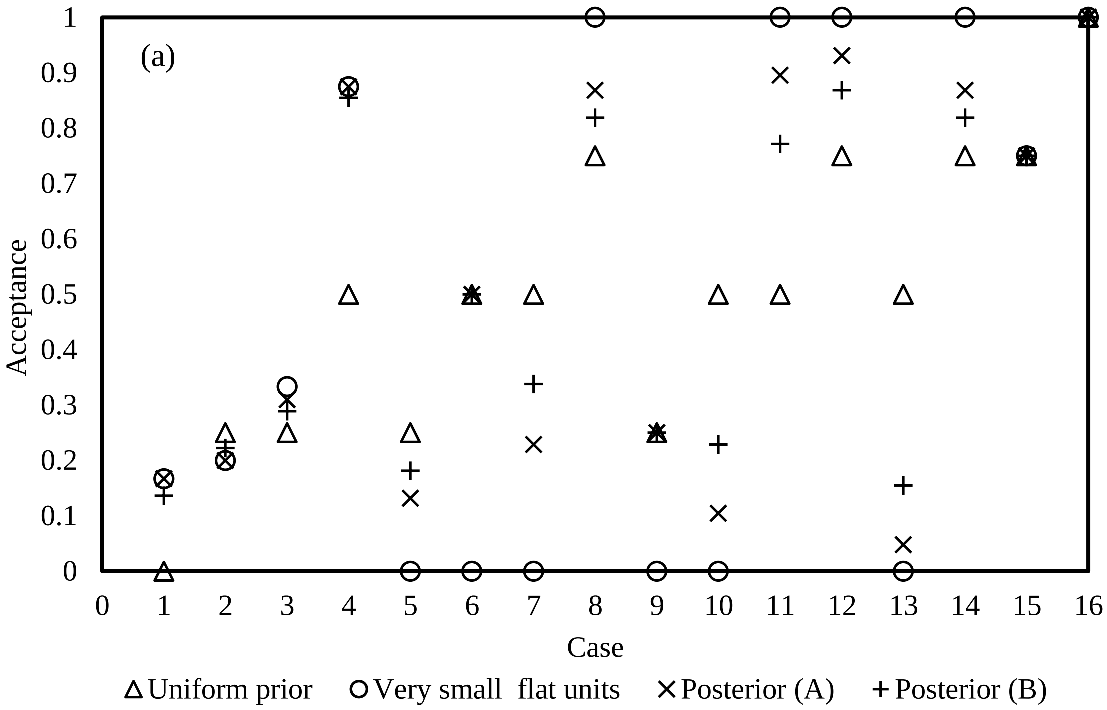
Table 5.2 exhibits the posterior acceptance (ρ_j') with (a) uniform prior and (b) probability of acceptance by regression model under managerial decisions choice A (N = 5, ε = 0.01) and choice B ($N = 10$, $\varepsilon = 0.01$). Figure 5.2 is the graphical presentation of the Bayesian estimations. It is noteworthy that in some cases no sample were recorded (i.e. $n = 0$, annotated with '$^{\sigma}$'), prior acceptance becomes the sole and the best information available for prediction, therefore the posterior acceptance is the same as prior acceptance (i.e. $\rho_{j,0} = \rho_j'$).

Table 5.2 Posterior acceptance with (a) uniform prior and (b) regression model under managerial decisions choice A (target sample size $N = 5$, acceptable error $\varepsilon = 0.01$) and choice B ($N = 10$, $\varepsilon = 0.01$)

Case	Very small flat units		(a) Uniform Prior			(b) Regression model		
				Posterior (ρ_j')			Posterior (ρ_j')	
j	n	Measured ($\rho_{j,n}$)	Prior ($\rho_{j,0}$)	A	B	Prior ($\rho_{j,0}$)	A	B
1	6	0.167	0	$0.167^{\#}$	0.136	2×10^{-15}	$0.167^{\#}$	0.136
2	5	0.2	0.25	$0.2^{\#}$	0.222	8×10^{-6}	$0.2^{\#}$	0.155
3	3	0.333	0.25	0.310	0.289	3×10^{-10}	0.292	0.217
4	8	0.875	0.5	$0.875^{\#}$	0.854	0.5	$0.875^{\#}$	0.854
5	1	0	0.25	0.132	0.181	$1\times10^{-14\tau}$	1×10^{-14}	1×10^{-14}
6^{σ}	0	–	0.5	0.5	0.5	4×10^{-5}	4×10^{-5}	4×10^{-5}
7	1	0	0.5	0.229	0.339	$2\times10^{-9\tau}$	2×10^{-9}	2×10^{-9}
8	1	1	0.75	0.869	0.819	0.83	0.904	0.872
9^{σ}	0	–	0.25	0.25	0.25	9×10^{-6}	9×10^{-6}	9×10^{-6}
10	2	0	0.5	0.105	0.229	0.9999	0.158	0.398
11	2	1	0.5	0.895	0.771	0.55	0.902	0.790
12	2	1	0.75	0.931	0.869	1^{*}	1	1
13	3	0	0.5	0.048	0.155	$5\times10^{-5\tau}$	5×10^{-5}	5×10^{-5}
14	1	1	0.75	0.869	0.819	0.9999^{τ}	0.9999	0.9999
15	4	0.75	0.75^{*}	0.75	0.75	0.86	0.766	0.792
16	13	1	1^{*}	$1^{\#}$	$1^{\#}$	1^{*}	$1^{\#}$	$1^{\#}$

$^{\tau}$–difference between prior acceptance and measured acceptance is smaller than the acceptable error; *–prior acceptance is the same as measured acceptance; $^{\#}$–sample size meets with the target sample size and therefore the posterior acceptance is equal to the measured acceptance.

Remark: Measured acceptance of cases with no sample (i.e. $n = 0$) is marked as "–". These cases are annotated with '$^{\sigma}$'. Column "ρ_j'" shows the posterior acceptance updated by Bayesian approach based on prior estimate ($\rho_{j,0}$) and measured acceptance ($\rho_{j,n}$) collected.



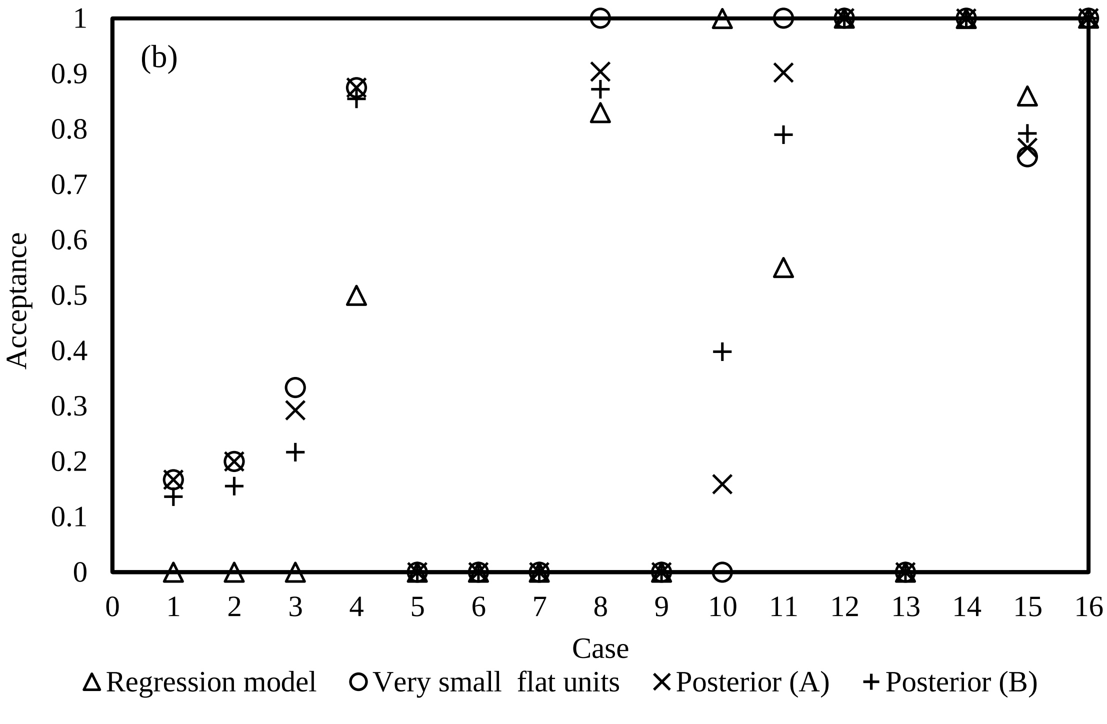


Figure 5.2 Graphical presentation of the Bayesian estimation of (a) IEQ model with uniform prior acceptance; (b) Multivariate logistic regression model for IEQ in average residential buildings (Lai, Mui et al., 2009)

When the sample size is small comparing to target sample size, e.g. case j = 5, 7, 8 and 14 of choice B, by Bayesian approach, survey data have small influences on the prior acceptance, resulting a posterior acceptance that is closer to prior than measured acceptance. On the other hand, for cases with larger sample sizes, e.g. case j = 15 of choice A and case j = 4 of choice B, influences of survey data on prior belief are larger and therefore posterior estimation is closer to measured acceptance. For cases which sample size is larger or equal to target sample size (annotated with '#'), i.e. $n \geq N$, e.g. case j = 1, 2, 4 and 16 of choice A and case j = 16 of choice B, the posterior estimate is equal to measured acceptance plus acceptable error (i.e. $\mu_N = \mu \pm \varepsilon$, where $\rho_j' \sim N(\mu', \sigma'^2)$). From the above, it can be seen that the target sample size significantly affects the resulting posterior estimations by Bayesian approach.

Some cases with measured acceptance equal to the prior belief (annotated with '*'), e.g. case j = 15 and 16 of uniform prior, case j = 12 and 16 of regression model, posterior acceptance is the same as the measured and the prior because the predicted and actual data agree with each other (i.e. if $\rho_{j,0} = \rho_{j,n}$, then $\rho_{j,0} = \rho_{j,n} = \rho_j'$). When the difference between measured acceptance and prior acceptance is equal or smaller than acceptable error (annotated with 'τ'), i.e. $|\mu_0 - \mu| \leq \varepsilon$ but $\neq 0$, e.g. case j = 5, 7, 13, and 14 of regression model, no significant difference between measured data and prior belief is considered, therefore posterior estimate is equal to prior belief. It is also recognizable that the selection of acceptable error greatly influences the estimations. For a large error, accuracy of the model is lower because a large difference between survey data and prior belief is accepted as measurement error, and therefore failing to update the prior with actual occupant's response.

5.4. Bayesian updating for thermal comfort model

Thermal comfort has always been the most discussed topic in IEQ. Given a number of thermal comfort model developed, Fanger's PMV/PPD model remains the most generally accepted, despite the acknowledgement of performance gap in PMV/PDD model by many thermal comfort field surveys. Some adjustments and modifications have been proposed to improve the accuracy, reliability and applicability of the model, they however seem to be unable to generalize the original PMV model and make it applicable to all types of environment and all kinds of people. The original PMV model is still the most cited one and widely adopted in building research and design reference.

To improve the prediction accuracy of existing PMV/PPD model in a particular setting, this sub-chapter attempts to propose two Bayesian updating protocols to systematically update the PMV–PPD belief. With thermal comfort field data openly available in literature, Bayesian approach allows the update of pre-established thermal sensation-satisfaction relationship with newly observed field data, which reflects and represents the effects of particular field settings and occupant's perceptions on thermal satisfaction. Occupant's subjective elements can therefore be incorporated into PMV/PPD relationship, which was developed entirely based on reductive physicalism of causal relationship of sensation and satisfaction.

5.4.1. Thermal comfort database

Thermal comfort database selection aims to demonstrate the percentage effects of field data sample size (n) on target sample size (N) under the Bayesian approach. A total of 4 thermal comfort datasets, outlined in Table 5.3, were selected for the demonstration: 1) residential buildings in Hainan, China (n = 1944) (Lu, Pang et al., 2018); 2) hospitals in Bangkok, Thailand (n = 928) (Sattayakorn, Ichinose et al., 2017); 3) elderly homes in Shanghai, China (n = 672) (Jiao, Yu et al., 2017); and 4) residential buildings in Hong Kong, China (n = 177) (Lai, Mui et al., 2009, Mui, Tsang et al., 2019).

Showing typical field survey results, all datasets have votes heavily concentrated (about 78%) in the range from -1 to +1; and their percentages of extreme votes (i.e. -3 and +3) are all below 10 % except for the +3 votes in Dataset 4. In Table 5.3, the PMV values (corresponding to each TSV) were calculated using the correlation coefficients C_1 and C_0, while APD as measured acceptance (μ) and the sample size of each TSV (n), with PPD (corresponding to each PMV) as the prior acceptance (μ_0), were used to compute the posterior acceptance (μ').

Table 5.3 Selected databases for Bayesian thermal comfort model demonstration

Reference	Sample size (n)	C_1	C_0		TSV						
					-3	-2	-1	0	1	2	3
Lu, Pang et al. (2018)	1944	0.94	-0.31	n	–	–	–	–	–	–	–
				PMV	-2.86	-1.80	-0.73	0.33	1.39	2.45	3.51
				APD (%)	8.7	2.3	2.8	2.8	19.3	23.2	40.9
Sattayakorn, Ichinose et al. (2017)	451 (Patient)	0.52	0.004	n	5	45	74	255	41	25	6
				PMV	-5.79	-3.86	-1.93	-0.01	1.92	3.85	5.78
				APD (%)	66.2	31.5	8.5	0	3.1	9.2	22.3
	146 (Staff)	1.24	-0.98	n	8	27	45	25	20	14	7
				PMV	-1.64	-0.83	-0.02	0.79	1.60	2.41	3.21
				APD (%)	91.5	62.3	26.2	7.7	11.5	23.1	38.5
	331 (Visitor)	0.63	0.05	n	8	36	61	182	26	18	0
				PMV	-4.86	-3.27	-1.68	-0.08	1.51	3.10	4.70
				APD (%)	71.5	34.6	8.5	0	2.3	6.2	16.2
Jiao, Yu et al. (2017)	342	0.60	0.39	n	1	52	33	212	43	1	0
				PMV	-5.68	-4.00	-2.33	-0.66	1.01	2.69	4.36
				APD (%)	100	94	79	0	7	100	NA
	330	0.37	0.04	n	0	0	11	188	82	46	3
				PMV	-8.14	-5.46	-2.78	-0.10	2.58	5.26	7.94
				APD (%)	NA	NA	27	0	84	87	100
Lai, Mui et al. (2009) Mui, Tsang et al. (2019)	177	2.49	-0.02	n	0	2	15	76	47	12	25
				PMV	-1.20	-0.80	-0.39	0.01	0.41	0.81	1.21
				APD (%)	NA	50	0	0	8.51	66.7	100

Remark: PMV values (corresponding to each TSV) were calculated using the correlation coefficients C_1 and C_0; '–' indicates that TSV values are not available; 'NA' due to 0 sample size under the vote.

5.4.2. Procedures, results and practical implications

Two updating protocols, namely individual and global, are proposed to update the current PMV/PPD belief. Since individual updating uses one single dataset to update the prior belief, the sample size of each TSV is required (Datasets 2–4). This kind of updating, which is based on both prior information (PMV–PPD relationship) and new information (survey data), generates a unique relationship between PMV and PD of a particular environmental setting.

Figure 5.3 shows the posterior PD estimated by the updated Bayesian thermal comfort model. With a selected acceptable error $\varepsilon = 0.001$ (i.e. 0.1%) and a target sample size $N = 1000$, posterior estimation of PD can be computed using Equations 5.4–5.7. Results show that the posterior PD estimated is always closer to the measured APD than PPD. If the sample size n of each vote is significant comparing to the target sample size N, the posterior estimate will be closer to the APD. This can be observed generally at vote = 0, since most of the environments are designed to provide comfort for occupants. On the other hand, the sample size of an extreme vote (i.e. -3 or +3) is usually small, therefore the posterior PD is closer to PPD instead. As Bayesian estimation can evaluate the significance of a small dataset (as small as a one-sample dataset) and update the prior belief (the PPD in this case), the reliability concerns in regression analysis when the extreme vote sample size is too small are eliminated (Wong, Mui et al., 2014). This individual updating protocol gives a thermal comfort model that incorporates the adaptive and contextual parameters from occupants in a specific type of environment (or even as specific as from a particular environment). After updating with available field data, the posterior PD can act as an updated tailor-made model for further thermal comfort study.

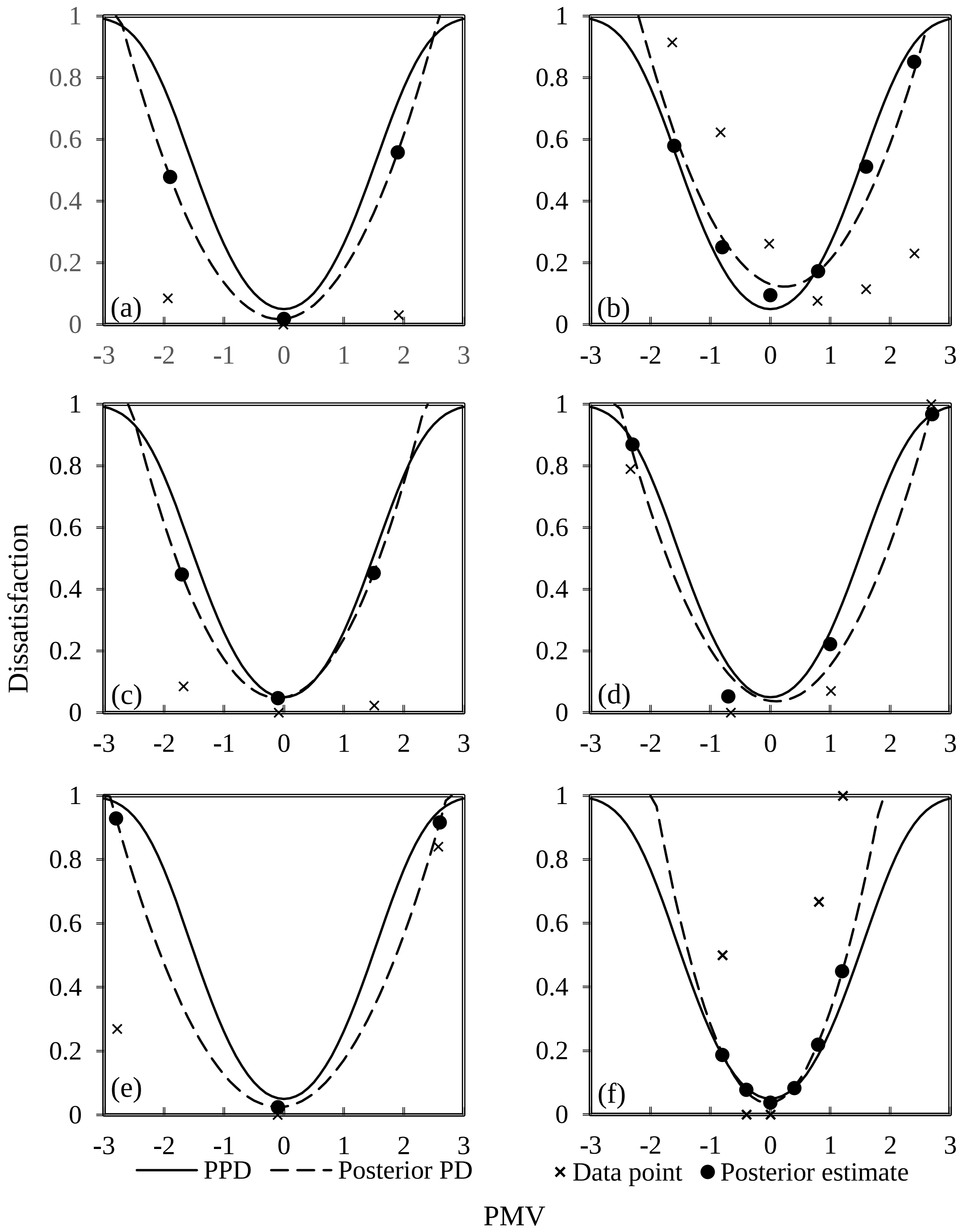


Figure 5.3 Posterior PD by Bayesian thermal comfort model using individual updating method with ε = 0.001 and N = 1000; (a) Patient, (b) Staff, (c) Visitor (Sattayakorn, Ichinose et al., 2017); (d) Winter, (e) Summer (Jiao, Yu et al., 2017); (f) Residential (Lai, Mui et al., 2009, Mui, Tsang et al., 2019)

Global updating treats each dataset as one sample and updates the PPD belief for a general indoor environment rather than a particular environmental setting. Presently, PMV/PPD based comfort standard is widely used regardless of the type of environment. Although contextual factors and adaptive behaviours strongly influence thermal comfort acceptability, modelling thermal comfort for each unique environment is resource demanding as field data collection is inevitable. By adopting the PMV/PPD concept, global updating can update the PPD belief using field data from different environments to generate a model that incorporates the influence of field settings on thermal comfort. Figure 5.4 graphs the posterior PD estimated by the Bayesian thermal comfort model with acceptable error $\varepsilon = 0.05$ and different target sample size $N = 5$, 10 and 20 to demonstrate the effects of target sample size difference. It can be seen that since one vote is regarded as one sample, when sample size is considered small and less significant compared to a pre-set target number (in case of $N = 20$), the posterior estimates are closer to the prior PPD belief (i.e. Fanger's as demonstrated) than the actual field data. With a smaller target sample size (in case of $N = 5$), Bayesian estimate will give an updated PMV/PPD model that makes prediction closer to actual data than the original model. Figure 5.4 demonstrates that Bayesian updating can significantly improve prediction quality.

To further illustrate the practical implications of using Bayesian updating, the proposed global protocol was applied to the GSHP study by Fang, Feng et al. (2018) discussed in Chapter 3, with error $\varepsilon = 0.05$ and target sample size $N = 10$. Showing a PMV range from -0.062 to +0.062 for having 5% thermally dissatisfied people, the updated PMV–PPD relationship was found to be slightly narrower than the original PMV–PPD. As a result, the minimum power consumption would be approximately 1.46kW at a PMV of -0.062.

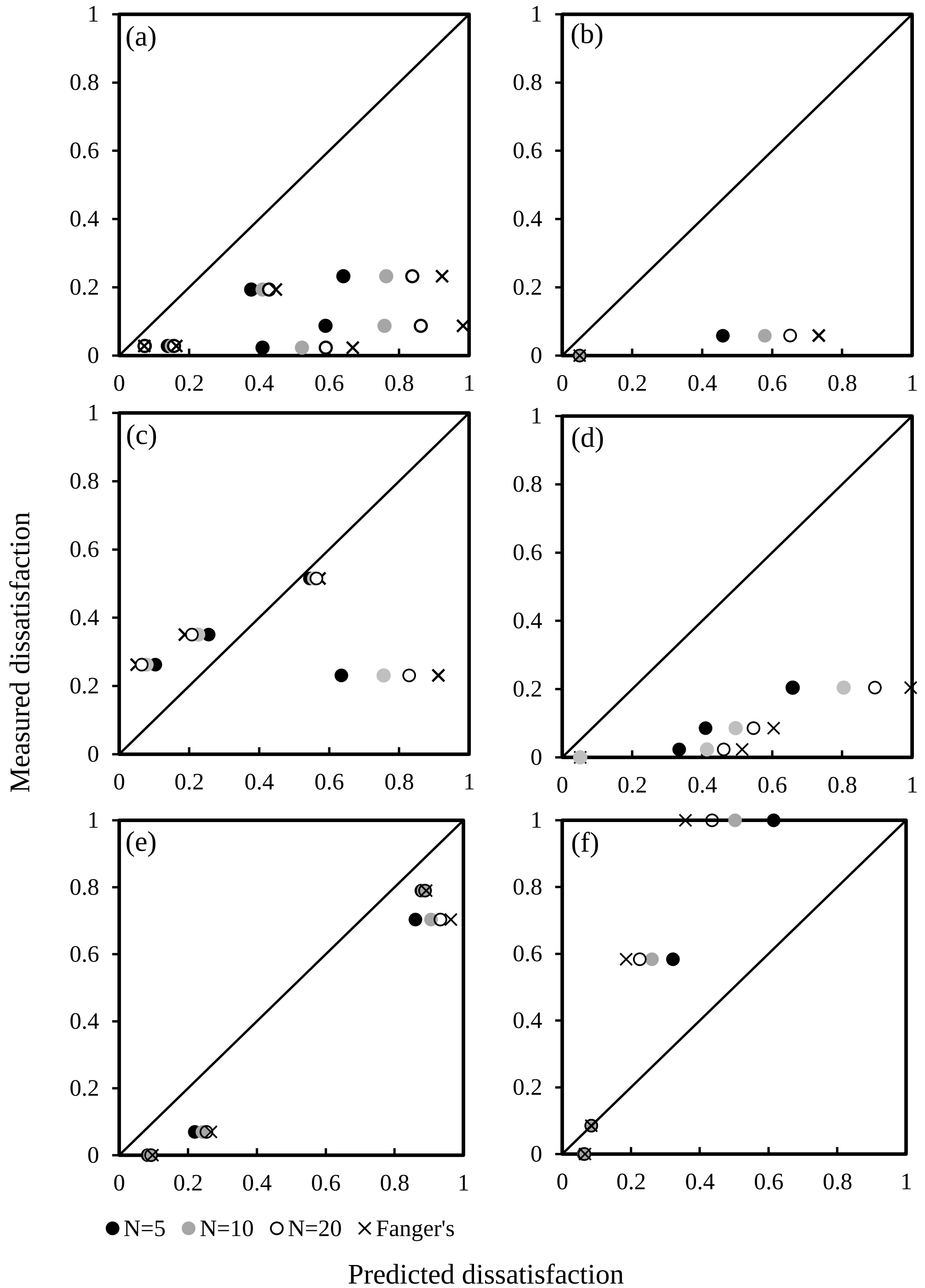


Figure 5.4 Posterior PD by Bayesian thermal comfort model with ε = 0.05 and N = 5, 10 and 20; a) Residential (Lu, Pang et al., 2018); (b) Patient, (c) Staff, (d) Visitor (Sattayakorn, Ichinose et al., 2017); (e) Elderly home (Jiao, Yu et al., 2017); (f) Residential (Lai, Mui et al., 2009, Mui, Tsang et al., 2019)

5.5. Summary

Assessing IEQ cannot solely rely on objective tools or subjective surveys. Thermal comfort and overall IEQ field studies revealed that occupant's responses towards a similar environment can be different due to their own perceptions and/ or adaptions. Considering occupant's perceptions towards an environment as a causal, reducible relationship may be easier for setting up guidelines and comfort requirements, but it may not truly reflect the actual experience (Willems, Saelens et al., 2020). The fundamental problem is that the pre-established models are derived from previous subjective-objective studies, and the relationship between subjective votes and objective physical measurements may change with different group of occupants. The perceptions toward environmental conditions and the above-mentioned relationship can change over time and with lived experience even with the same group of people.

Accurate subjective-objective thermal comfort and overall IEQ prediction models are therefore crucial for building engineers to predict occupant's satisfaction. They are also necessary for other related indoor environment research. Existing models are not yet comprehensive enough to give accurate environmental acceptance predictions. Previous research efforts for model modifications are restricted in terms of application. Given that the performance gap between actual field data and model predictions can lead to substantial errors and uncertainties in research, it is essential for existing prediction models to be updated based on new observations in field.

In order to overcome these research obstacles that may lead to further errors in related indoor research, a novel Bayesian approach for model updating is proposed in this chapter. Bayesian approach benefits IEQ modeling by allowing easy updating with newly acquired data, which handles the limitations of existing IEQ models. In addition, this approach is not limited to continuous IEQ parameters, discrete parameters that can be used to anticipate IEQ acceptance can also be processed by Bayesian approach if field data is available.

This chapter demonstrates two examples of Bayesian updating using highly cited PMV/PPD model and IEQ regression model. Two Bayesian updating protocols, namely individual and global, are presented to systemically update current PMV–PPD beliefs with openly available field data. Bayesian updating of previous residential IEQ model is also demonstrated by using subjective IEQ responses from very small units as inputs.

This method provides a systematic approach to related additional survey data to current belief. With selected target sample size and acceptable error, statistical significances of data are considered and incorporated into Bayesian analysis. It shows that the posterior acceptance is close to prior belief when the sample size is small. With large sample size, the posterior is instead close to the measured acceptance. For sample size that meets with the target sample number, posterior is equal to measured acceptance plus acceptable error. Updating of prediction models can therefore be achieved even with a small quantity of field data from a similar environment.

The proposed Bayesian updating protocols shall provide a general analytical solution for thermal comfort and overall IEQ modelling, which could be a useful tool for indoor environmental design with a selection of target sample size and acceptable error based on managerial decision. It also helps to improve model prediction accuracy by updating it with newly available observations on the relationship between environmental quantities and occupant's responses, before any holistic data-driven prediction model that can resolve the epistemic nature of occupant's perception is developed.

Chapter 6. Development of step-wise IAQ screening strategies protocol and IoT-based IAQ sensing network

6.1. Introduction

Modern people spend over 90% of their time indoors (Burroughs and Hansen, 2004). Maintaining an acceptable IAQ is therefore of utmost importance to protect the health of the general public. In view of the increasing IAQ concerns and complaints, there is an urgent need for a practical yet economical diagnostic tool for proper IAQ management.

Unlike other IEQ aspects which are easily detected by sense and mainly affect one's comfort with small chance of posing health consequences, IAQ can cause severe health problems, therefore shall not solely rely on subjective sense to determine the IAQ performance of an indoor environment. Objective-criteria approach can ensure the provision of a healthy environment.

Traditional IAQ assessment methods involve measuring a number of IAQ parameters and comparing them against a set of standards or health objectives. However, conducting a full IAQ assessment requires vast amount of resources and manpower. To minimize the need for and the cost of a comprehensive IAQ assessment, surrogate indicators approach provides an alternative to assess IAQ in air-conditioned offices. The concentration of three independent yet closely related IAQ parameters, namely CO_2, PM, and TVOC, was proposed to predict IAQ dissatisfaction without assessing other IAQ parameters (Wong, Mui et al., 2006). Further to that, an IAQ surveillance protocol, IAQ index, was proposed by Wong, Mui et al. (2007) for identifying asymptomatic IAQ problems in offices. This screening test was proven to provide a much simpler and cost-effective alternative for IAQ assessment.

IAQ screening tools reduce the cost and resources required for IAQ assessment, which is beneficial for large-scale IAQ screening to understand the overall IAQ situation in the region. Still, IAQ problems cannot be identified instantaneously, leaving occupants prone to IAQ-related sicknesses and diseases.

Build upon the idea of screening strategies proposed by (Wong, Mui et al., 2007), this chapter investigates the use of different combinations of dominant IAQ parameters in a step-wise IAQ screening protocol for identifying undesirable IAQ with engineering acceptable accuracy. A simple and economical decision-making framework for IAQ monitoring and mitigation is proposed to facilitate IAQ management. To demonstrate and evaluate the feasibility of using low-cost IAQ sensors to monitor and screen potential risks of problematic IAQ, a large-scale IoT-based IAQ screening is conducted in a multifunctional shopping mall to collect spatial and temporal IAQ information. Environmental attributes that contribute to poor IAQ are determined. This chapter aims to present a holistic IAQ monitoring framework for cost-beneficial IAQ management with minimum resources.

6.2. Concept of screening strategy

Adopting the threshold approach for screening test decision making proposed by Pauker and Kassirer (1980), the post-test probability of unsatisfactory IAQ determined by IAQ screening test indicates the level of required action. If it falls below the testing threshold (also known as the no action threshold), no action is required for maintaining the current IAQ level since it is considered as acceptable. If the post-test probability is beyond test-treatment threshold, immediate remediation should be given to improve the IAQ level. Further tests should only be performed if the post-test outcome falls between the two thresholds, indicating an uncertain result that requires subsequent investigations. All the thresholds are predetermined based on resource and health considerations.

Using the concept of IAQ index described in Equation 2.7, the IAQ assessment framework proposed here uses a step-wise IAQ screening protocol that involves different screening stages where additional IAQ parameters can be included in the index calculation. Three IAQ indices, namely θ_1 (with one parameter: CO_2), θ_2 (with two parameters: CO_2 and PM_{10}), and θ_3 (with three parameters: CO_2, PM_{10}, and TVOC) are proposed. Figure 6.1 illustrates the framework of the screening and decision-making process for IAQ management under this approach. Likelihood ratio, indicted in Equation 2.8, assesses the ability of the screening test in diagnosing problematic IAQ. A likelihood ratio larger than 1 indicates a high-risk sample having an excessive occurrence of unsatisfactory IAQ, whereas a likelihood ratio smaller than 1 identifies a low risk sample. The likelihood ratio of an IAQ index in diagnosing unsatisfactory IAQ can be determined by Equation 2.9, given an available comprehensive IAQ assessment database as reference.

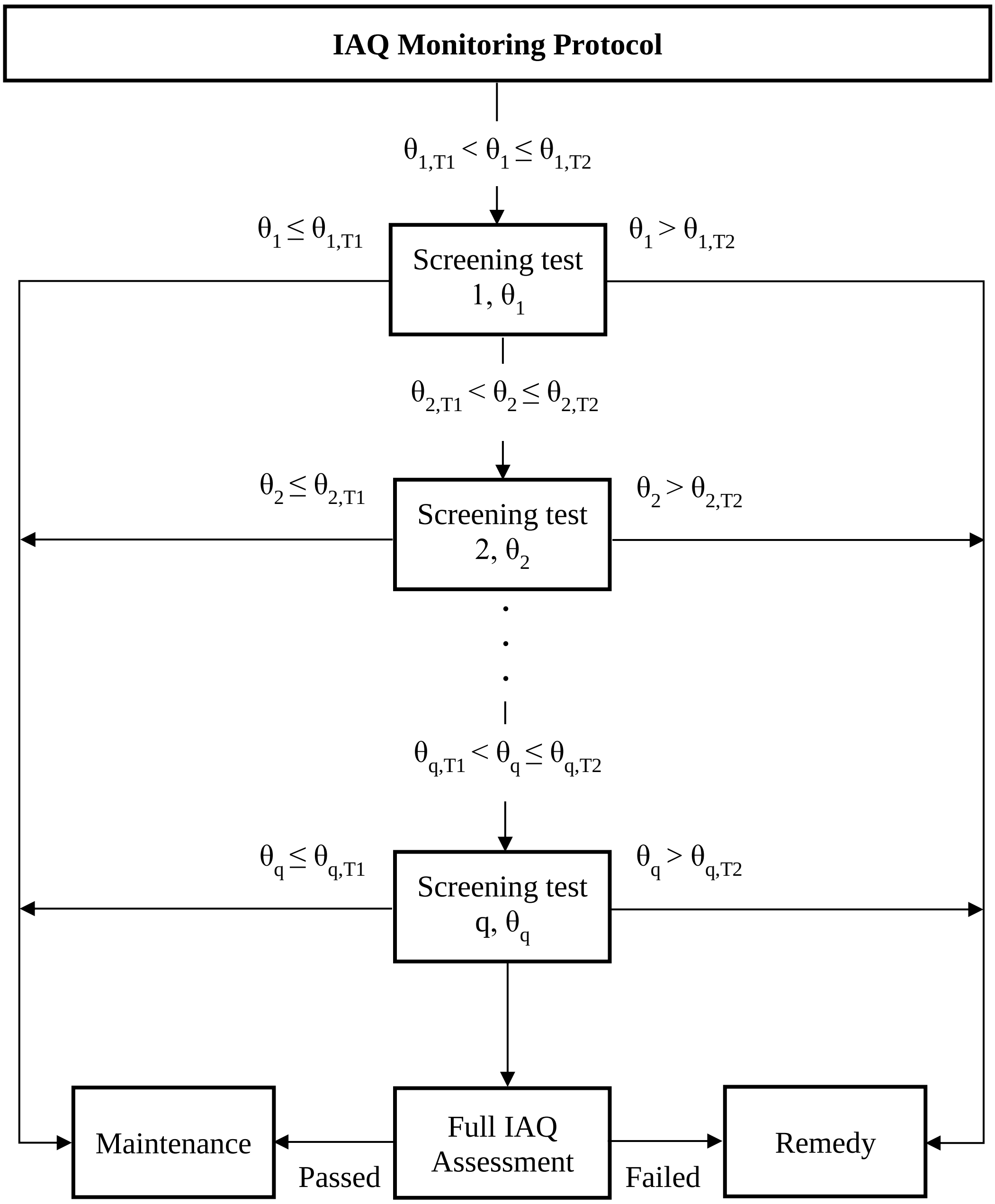


Figure 6.1 Screening and decision-making framework for IAQ assessment using step-wise IAQ screening protocol

6.2.1. IAQ assessment dataset

To demonstrate the proposed step-wise IAQ screening approach, IAQ Dataset A containing a total of 525 random samples of Hong Kong air-conditioned open-plan offices with similar building materials, style and age is taken from some previous studies (Hui, Wong et al., 2006, Mui, Hui et al., 2011). Surveyed locations include individual offices and conference rooms with the size of 10–300 m^2. 358 of them fulfill the Good Class exposure limits stated in IAQ Certification Scheme. This database is adopted to determine the screening levels (i.e., thresholds) of three different IAQ indices (i.e., θ_1, θ_2, and θ_3) for assessing Hong Kong air-conditioned offices based on the likelihood ratio of having unsatisfactory IAQ.

IAQ Dataset B consists of 2248 offices IAQ data randomly collected from various IAQ investigations conducted in the year 2008, covering a diverse range of regions, building grades and sizes, therefore is able to represent the overall IAQ situation in Hong Kong offices. Among them, 2002 offices meet the criteria for Good Class. This database serves as a comprehensive dataset for demonstrating and evaluating the feasibility and effectiveness of the proposed step-wise screening strategies for IAQ pre-assessment.

Table 6.1 summarizes the pairwise comparison of the two datasets, showcasing the arithmetic means, arithmetic standard deviations, and expected failure rates of the nine indoor air pollutants against the respective 8-hr exposure limits recommended by the Scheme. High failure rates are observed for CO_2 and TVOC in both Dataset A and B, suggesting those are common problems identified in Hong Kong office. PM_{10}, NO_2, HCHO, TVOC, Rn, and ABC in Dataset A are significantly different from those in Dataset B (p-value ≤ 0.05, t-test). The rest show no difference. No correlation is shown between the two datasets, indicating independency. The IAQ dissatisfaction rates for office in Dataset A and B are 32% and 11% respectively.

Table 6.1 IAQ assessment data for air-conditioned offices in Hong Kong

Parameter	Unit	8-hr Exposure Limit	Database A AM (SD) [EFR%]	Database B AM (SD) [EFR%]	p-value
CO_2	ppm	1000	658 (151) [7%]	665 (203) [50%]	0.17
CO	$\mu g/m^3$	10,000	1105 (4594) [1%]	1372 (825) [1%]	0.09
RSP	$\mu g/m^3$	180	30 (20) [0%]	27 (30) [3%]	$\leq$0.05
NO_2	$\mu g/m^3$	150	27 (17) [0%]	33 (14) [0.4%]	$\leq$0.05
O_3	$\mu g/m^3$	120	40 (38) [13%]	40 (19) [3%]	0.39
HCHO	$\mu g/m^3$	100	48 (103) [15%]	29 (22) [13%]	$\leq$0.05
TVOC	$\mu g/m^3$	600	358 (328) [42%]	176 (176) [24%]	$\leq$0.05
Rn	Bq/m^3	200	46 (39) [0.6%]	68 (41) [6%]	$\leq$0.05
ABC	CFU/m^3	1000	505 (385) [38.4%]	238 (175) [6%]	$\leq$0.05

AM–arithmetic means; SD–arithmetic standard deviations; EFR–expected failure rate.

6.2.2. Illustration of IAQ indices

Likelihood ratios for unsatisfactory IAQ identification using IAQ indices θ_1, θ_2, and θ_3 are compared with the assessment results by IAQ Certification Scheme. The three indices are categorized into five screening levels based on the testing thresholds (i.e., multilevel likelihood ratios with an order of magnitude of 10 or 0.1) used in medical test for diagnoses (Sackett, Straus et al., 2000). Except for θ_1, each level consists of at least five samples to ensure statistical significance. The intermediate levels are distributed evenly for consistency so that direct comparisons can be made.

Table 6.2 exhibits the screening test results and the corresponding likelihood ratios for IAQ indices θ_1, θ_2, and θ_3. The sensitivity and specificity of screening test increase when more surrogate parameters are incorporated into the index calculation, and an IAQ diagnosis using fewer parameters increases uncertainty of the pre-assessment.

Table 6.2 IAQ index screening levels for unsatisfactory IAQ in air-conditioned Hong Kong offices

Screening Level for θ_1, θ_2, θ_3	Unsatisfactory IAQ Counts (%)			Satisfactory IAQ Counts (%)			Likelihood Ratio (L_r)		
	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3
<0.32	0 (0%)	11 (6.6%)	5 (3%)	0 (0%)	74 (21%)	93 (26%)	/	0.3	0.1
0.32–0.42	1 (0.6%)	64 (38%)	24 (14%)	10 (2.8%)	165 (46%)	131 (37%)	0.2	0.8	0.4
0.43–0.53	19 (11%)	61 (37%)	33 (20%)	62 (17%)	96 (27%)	85 (24%)	0.7	1.4	0.8
0.54–0.64	47 (28%)	23 (14%)	33 (20%)	116 (32%)	19 (5%)	43 (12%)	0.9	2.6	1.7
≥0.65	99 (59%)	8 (4.8%)	72 (43%)	161 (45%)	4 (1%)	6 (1.7%)	1.3	4.3	25
Total count	167 (100%)			358 (100%)					

The post-test probabilities of selected likelihood ratios for IAQ indices θ_1, θ_2, and θ_3 against pre-test probabilities ranging from 0.1 to 0.7 for air-conditioned offices are illustrated in Figure 6.2. Pre-test and post-test probability can be calculated using Equation 2.10 and 2.11. The post-test probabilities given by the three IAQ indices indicate the probabilities of having an unsatisfactory IAQ, it is therefore necessary to set the boundaries for each screening level using a post-test probability that is significantly high or low in order to rule out most uncertainties. To ensure the screening test can diagnose most unsatisfactory IAQ, thresholds of screening level should be set with maximum sensitivity, but the specificity of the screening test will unavoidably be lower (Gilbert, Logan et al., 2001).

For practical uses, numerical post-test probabilities are translated into verbal probability expressions (VPEs) to describe the quantitative concepts (Reagan, Mosteller et al., 1989, Vick, 2002). Screening levels are therefore expressed as follow:

1. Very improbable ($P_d' \leq 0.05$);
2. Improbable (P_d' = 0.05–0.2)
3. Possible (P_d' = 0.2–0.4);
4. Probable (P_d' = 0.4–0.7);
5. Very probable (P_d' = 0.7–0.9); and
6. Almost certain ($P_d' > 0.9$).

At $L_r = 25$ (i.e., the highest likelihood ratio), θ_3 is highly sensitive in identifying unsatisfactory IAQ cases ranging from “4. Probable” to “6. Almost certain”, while θ_1 is the least sensitive. θ_2 can identify most cases of higher than average unsatisfactory IAQ.

At $L_r = 0.1–0.3$ (i.e., the lowest likelihood ratios), all of the three IAQ indices can identify "improbable" cases with pre-test failure rate up to 0.4. For instance, the screening results of a pre-test "improbable" case ($P_d = 0.15$, indicated by line) for θ_1, θ_2, and θ_3 are "2. Improbable", "3. Possible", and "5. Very probable", respectively at highest likelihood ratio of tests, while at lowest likelihood ratio, all tests result in "1. Very improbable". The case of a pre-test "Possible" ($P_d = 0.35$) is also illustrated in Figure 6.2 for comparison.

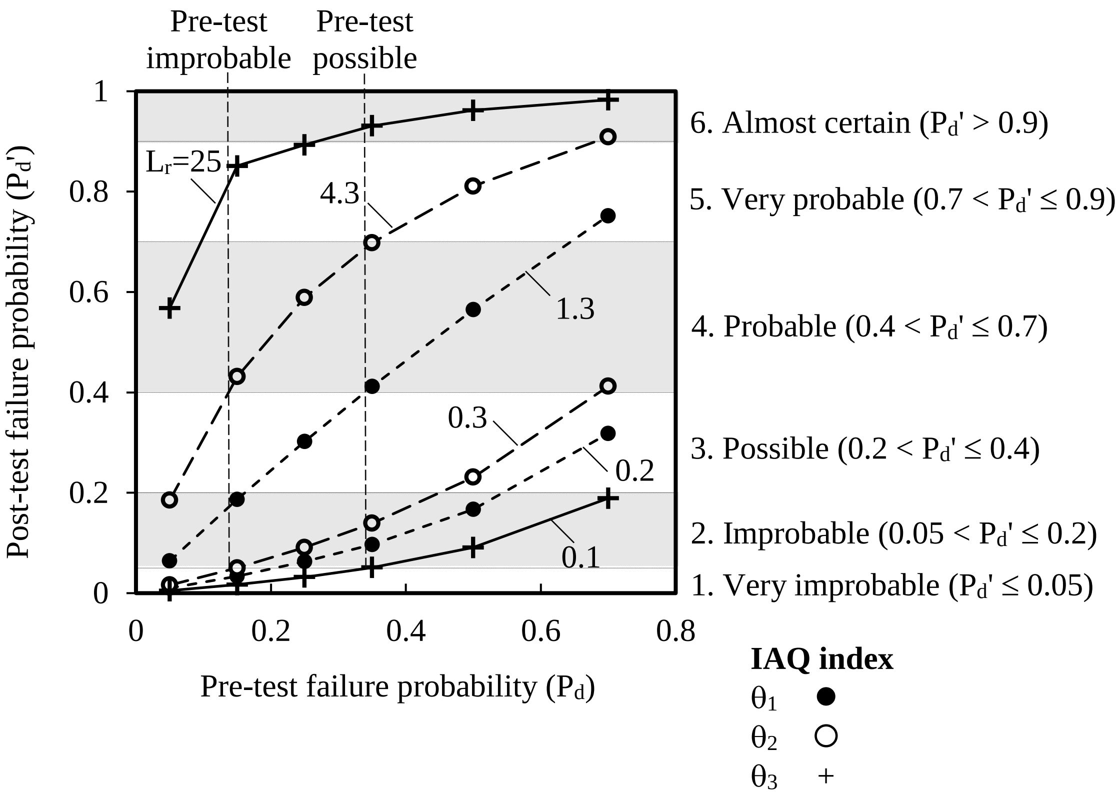


Figure 6.2 Pre- and post-test probabilities with IAQ indices θ_1, θ_2, and θ_3

6.3. Performance of IAQ screening strategies

Table 6.3 presents Dataset B screening results using IAQ indices θ_1, θ_2, and θ_3. Two pre-test probabilities representing two different scenarios of regional IAQ dissatisfaction rate, $P_d = 0.35$, corresponds to "3. Possible", a higher pre-test failure rate, and $P_d = 0.15$, "2, improbable", a compatible pre-test failure rate suggested by Dataset B, are adopted. For each screening level, the failure probability P is calculated based on the IAQ Certification Scheme (i.e., a full test) using the true positive (dissatisfaction) counts (n_u) over the total number of offices (n) in the screening level. Test results show that, in general, by assuming one rank higher in the pre-test failure probability rankings, the corresponding post-test results are of one rank higher as compared with the full test results. When a compatible pre-test probability assumed, the assessment results of the screening test are very similar to the full test.

Looking at the distribution assessment class of the screening levels, it can be seen that the resolution of the IAQ index θ_1 is relatively low, as the assessment results involve only two to three out of six VPEs. IAQ index θ_1 can only identify a small group of samples (183 out of 2248 offices) that are with lower chance of having unsatisfactory IAQ. On the other hand, screening using IAQ indices θ_2 and θ_3 give assessment results with higher resolutions, involving three to four out of six VPEs. IAQ indices with more parameters can identify not only the lower risk groups, but also the higher risk ones.

Table 6.3 Screening levels and assessment results of 2248 offices using IAQ indices

Screening Level	L_r	n	(i) Screening Test (P_d = 0.35)			(ii) Screening Test (P_d = 0.15)			Full Test	
			O_d'	P_d'	Assessment Result	O_d'	P_d'	Assessment Result	P	Assessment Result
(a) θ_1										
0.32–0.42	0.2	183	0.11	0.10	2. Improbable	0.04	0.03	1.Very improbable	0.03	1. Very improbable
0.43–0.53	0.7	444	0.38	0.27	3. Possible	0.12	0.11	2. Improbable	0.05	1. Very improbable
0.54–0.64	0.9	521	0.49	0.33	3. Possible	0.16	0.14	2. Improbable	0.07	2. Improbable
≥0.65	1.3	1100	0.70	0.41	4. Probable	0.23	0.19	2. Improbable	0.17	2. Improbable
(b) θ_2										
<0.32	0.3	510	0.16	0.14	2. Improbable	0.05	0.05	2. Improbable	0.05	1. Very improbable
0.32–0.42	0.8	870	0.43	0.30	3. Possible	0.14	0.12	2. Improbable	0.05	1. Very improbable
0.43–0.53	1.4	570	0.76	0.43	4. Probable	0.25	0.20	3. Possible	0.07	2. Improbable
0.54–0.64	2.6	211	1.40	0.58	4. Probable	0.47	0.32	3. Possible	0.42	4. Probable
≥0.65	4.3	87	2.32	0.70	4. Probable	0.76	0.43	4. Probable	0.56	4. Probable
(c) θ_3										
<0.32	0.1	865	0.05	0.05	1. Very improbable	0.02	0.02	1. Very improbable	0.02	1. Very improbable
0.32–0.42	0.4	819	0.22	0.18	2. Improbable	0.07	0.07	2. Improbable	0.03	1. Very improbable
0.43–0.53	0.8	327	0.43	0.30	3. Possible	0.14	0.12	2. Improbable	0.16	2. Improbable
0.54–0.64	1.7	144	0.92	0.48	4. Probable	0.30	0.23	3. Possible	0.56	4. Probable
≥0.65	25	93	13.5	0.93	6. Almost certain	4.41	0.82	5. Very probable	0.74	5. Very probable

Figure 6.3 compares the full test unsatisfactory rates with post-test failure probabilities by IAQ indices. The screening tests give good predictions in general, with IAQ indices θ_2 and θ_3 better at identifying the high-risk groups for unsatisfactory IAQ. Estimating a higher pre-test failure probability results in overestimation of failure probability by screening test.

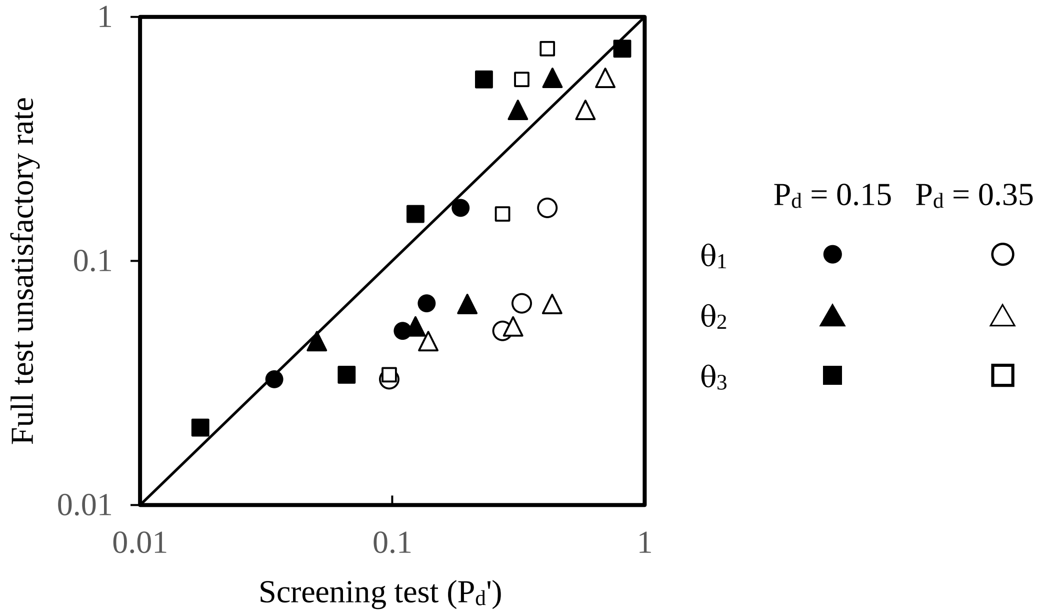


Figure 6.3 Full test unsatisfactory rates versus post-test failure probabilities by IAQ indices

To demonstrate the predictive and problem identification abilities of the step-wise IAQ screening protocol illustrated in Figure 6.1, Dataset B is screened again consecutively using different combinations of IAQ indices. The screening results with P_d = 0.35 and 0.15 are summarized in Table 6.4. Results from the first screening test (Table 6.3) using IAQ indices individually are also shown for reference.

Table 6.4 IAQ classifications for 2248 offices using step-wise IAQ screening protocol

Screening Tests	No. of offices with predicted unsatisfactory IAQ (Unsatisfactory rate)													
	1. Very Improbable ($P_d' \leq 0.05$)		2. Improbable ($0.05 < P_d' \leq 0.2$)		3. Possible ($0.2 < P_d' \leq 0.4$)		4. Probable ($0.4 < P_d' \leq 0.7$)		5. Very probable ($0.7 < P_d' \leq 0.9$)		6. Almost Certain ($P_d' > 0.9$)		Thresholds $0.05 < P_d' \leq 0.9$	Thresholds $0.2 < P_d' \leq 0.9$
	n	P	n	P	n	P	n	P	n	P	n	P	n	P
$P_d = 0.35$														
θ_1			183	0.03	965	0.06	1100	0.17					2248	2065
θ_2			510	0.05	870	0.05	868	0.20					2248	1738
θ_3	865	0.02	819	0.03	327	0.16	144	0.56			93	0.74	1290	471
(a) θ_1, θ_2	126	0.05	435	0.04	872	0.06	741	0.18	74	0.59			2122	1687
(b) θ_1, θ_3	737	0.02	448	0.06	837	0.09	133	0.58	3	1	90	0.73	1421	973
(c) θ_2, θ_3	852	0.02	407	0.04	630	0.04	190	0.31	80	0.76	89	0.73	1307	900
(d) $\theta_1, \theta_2, \theta_3$	760	0.03	544	0.03	475	0.04	291	0.21	92	0.73	86	0.72	1402	858
$P_d = 0.15$														
θ_1	183	0.03	2065	0.12									2065	0
θ_2			1380	0.05	781	0.16	87	0.56					2248	870
θ_3	865	0.02	1146	0.07	144	0.56			93	0.74			1383	237
(a) θ_1, θ_2	546	0.04	937	0.05	682	0.18	83	0.58					1702	765
(b) θ_1, θ_3	903	0.02	1119	0.06	133	0.58	3	1	90	0.73			1345	226
(c) θ_2, θ_3	945	0.02	968	0.05	166	0.27	80	0.76	35	0.89	54	0.63	1249	281
(d) $\theta_1, \theta_2, \theta_3$	1007	0.02	806	0.05	255	0.20	91	0.70	35	0.89	54	0.63	1187	381

Except for strategy (b) using IAQ index θ_1 first then θ_3 (i.e. screen with CO_2 first, then CO_2, PM_{10} and TVOC afterwards), where there is an underestimation in the intermediate risk group, the results show that by assuming one rank higher in the pre-test failure probability, the post-test assessment results are one rank higher than the full test results, and by assuming a compatible pre-test probability, the assessment results and full-test results are be compatible.

Threshold examples are proposed to represent stringent and lenient IAQ management requirements. All screening strategies successfully screen out some offices that do not require a full test to determine if the IAQ is satisfied or not, as a result reducing the resources required. Overall, the strategies are useful in ranking the offices based on the probability of having unsatisfactory IAQ, and therefore having the potential to facilitate cost-effective IAQ management.

6.4. IoT-based IAQ sensing network

Long-term IAQ surveillance is a state-of-art technique for continuously monitoring of the concentrations of indoor air pollutants. Unlike annual IAQ assessment, long-term monitoring can instantly reveal possible IAQ problems and identify any acute exposure to air pollutants which can be harmful to occupants. It also provides spatial characterizations and temporal understandings of IAQ of an environment, which aid the identification of emitting sources, problematic design layouts and building operation strategies, and the formulation of mitigation plans.

Long-term monitoring also allows instant intervention. Given the spatial resolution of IAQ profile revealed by the sensing network, ventilation strategies can be localized and therefore achieve higher energy efficiency (de Vito, Fattoruso et al., 2011). Marques, Roque Ferreira et al. (2018) demonstrated the use of Internet of Things (IoT) system for monitoring PM levels, enabling the scalability (the addition of more sensors) and flexibility (sensor mobility) of the system. With the IoT system, chronological history of PM levels can be retrieved, therefore assisting facility management to formulate strategies to enhanced IAQ standard. Long-term IAQ monitoring has been used in some developed places like Doha and Taiwan for maintaining good IAQ. Unfortunately, such technology still has not been implemented publicly in Hong Kong so far.

With increasing concern over IAQ, more and more building developers seek ways to maintain good IAQ for a healthy indoor environment for building users and tenants (NWD, 2019). In order to fulfil the industry demands, health risks of poor IAQ shall be addressed during daily building operation period. A long-term continuous monitoring of IAQ which reflects the health risks of building occupants is therefore deemed important.

Approached with an opportunity, the use of IoT-based low-cost IAQ sensing network for problematic IAQ screening was demonstrate in a newly constructed multifunctional mall with floor size of 5,000m^2 in Hong Kong. A total of 80 IAQ sensing modules were installed in various places on different floors of the mall in order to identify potential sources of air pollutants and recognize the effects of environmental attributes on IAQ. The modules collected IAQ data, including T_a, RH, PM_{10}, $PM_{2.5}$, CO_2, TVOC and CO, three times a day at 7am, 3pm and 11pm consecutively for 3 months covering spring and early summer of Hong Kong. Measured data were transmitted and stored in the Building Management System for processing into IAQ index for public display to customers in the mall. Table 6.5 displays the IAQ data collected in 3 months.

Table 6.5 3-month IAQ data collected by IoT-based monitoring system in a multifunctional mall in Hong Kong

Parameter	Max	Min	Average	SD
T_a (°C)	28.40	18.36	24.34	1.43
RH (%)	84.84	24.48	61.15	7.04
CO_2 (ppm)	1029.63	387.08	462.10	50.59
CO (µg/m^3)	2.31	0	0	0.03
PM_{10} (µg/m^3)	293.69	3.04	82.92	35.53
$PM_{2.5}$ (µg/m^3)	278.12	0.76	66.56	26.66
TVOC (ppm)	10$^{\#}$	0.04	0.64	1.32
IAQ index θ_2	1.04	0.21	0.46	0.10
IAQ index θ_3	19.70	0.32	1.70	2.53

$^{\#}$–Maximum detection limit of TVOC sensor.

Remark: Some data were screened out due to sensor/ signal problems.

Focusing on individual parameters, 2.1% of PM_{10} exceeded the Good Class exposure limit of 100µg/m^3. High PM_{10} was observed mostly on lower floor of the mall, with basement level suffered a higher chance of elevated PM_{10} than above-ground levels. 90% of high PM_{10} were discovered to be in food and beverage area, 70% in back of house corridor. To improve the PM_{10} situation, it was suggested to have more frequent cleanings in the food and beverage area and back of house corridor. The filter in ventilation system shall also be cleaned regularly. Additional air cleaner with HEPA filter can be adopted in area with high PM_{10} level.

For CO_2, there was only one data exceeded the Good Class level of 1000ppm, five exceeded the Excellent Class of 800ppm, with an overall average of 462.1ppm. As CO_2 is a surrogate indicator for ventilation efficiency, ventilation performance of shopping mall was considered to be excellent.

Alarmingly, over 50% of TVOC exceeded Good Class level of <261ppb, with an average of 640ppb. TVOC was higher in the morning than in the afternoon and at night, but in general high TVOC could be found in any time of a day. Basement suffered a higher chance of high TVOC than above-ground levels, and 80% of high TVOC were discovered in food and beverage area, 61% in back of house corridor. Compared to first week TVOC data, significantly lower TVOC were measured by 80% of sensors during the last measurement week. It is most likely that the emission from building materials and finishing was gradually dropping to a background level throughout the three-month measurement period. High TVOC could therefore be attributed to other environmental factors like location, function of the area, activities of the area, etc. Unusually high TVOC level could be the result of malfunctioning sensor or nearby TVOC generating activities, for example use of air freshener. Unfortunately, it was unable to pinpoint the causes of such high levels of TVOC in the mall through the above analysis. As a result, facility management of the mall was recommended to pay special attentions on those areas with high TVOC level to identify possible sources of pollutants and formulate mitigation strategies accordingly.

IAQ indices θ_2 and θ_3 calculated from the IAQ data are shown in Table 6.6. Since no IAQ Certification Scheme data for shopping mall was available from open literature, a pre-test probability could not be determined. As such, office pre-test probability of 0.35 was adopted. For IAQ index θ_2, the majority of them fell into the “2. Moderately negative” and “3. Slightly positive” rank of having dissatisfied IAQ, which was considered to be performing well in general. For IAQ index θ_3, over 95% of time the IAQ fell into “5. Very positive”, suggesting a very high chance of suffering from poor IAQ. Such alarming results suggested by IAQ index θ_3 could be attributed to unexpectedly high TVOC.

With such large volume of valuable spatial IAQ data, IAQ index θ_2 results were used to identify environmental attributes that contribute to poor IAQ. By determining the fail ratio of high-risk data (i.e. 4. Moderately positive and 5. Very positive) to overall sample of each environmental attributes, attributes with higher risk of problematic IAQ can be identified. Corresponding precautionary measures can therefore be formulated to prevent the occurrence of IAQ problems.

Table 6.6 IAQ index results of IAQ data collected by IoT-based monitoring system in a multifunctional mall in Hong Kong

	Screening level	Likelihood Ratio	Count	%	Result
θ_2	<0.32	0.3	1125	5.8%	1. Very negative
	0.32-0.42	0.8	6313	32.7%	2. Moderately negative
	0.43-0.53	1.4	8728	45.2%	3. Slightly positive
	0.54-0.64	2.6	1732	9.0%	4. Moderately positive
	>=0.65	4.3	1403	7.3%	5. Very positive
	NA		18		
	Total		19319		
θ_3	<0.32	0.1	0	0.0%	1. Very negative
	0.32-0.42	0.4	48	0.3%	2. Moderately negative
	0.43-0.53	0.8	212	1.1%	3. Slightly negative
	0.54-0.64	1.7	323	1.8%	4. Moderately positive
	>=0.65	25	17867	96.8%	5. Very positive
	NA		869		
	Total		19319		

Remark: Some data are missing due to sensor/ signal problems, annotated as "NA".

Environmental characteristics, for example above or below ground, food and beverage area, back of house area, supermarket, cosmetic store, near toilet and lobby, were investigated. *p*-value <0.01 by Chi-square tests between all pairs of characteristic suggested that the IAQ performances of different environment characteristics were significantly different. Table 6.7 shows the fail ratio of each pair of environmental attributes. It can be seen that basement area, food and beverage area, back of house, supermarket and cosmetic area had poorer IAQ, which could be due to the nature of the business and high occupancy. On the other hand, lobby and near toilet had better IAQ, which could be explained by higher natural and mechanical ventilation rate respectively.

Table 6.7 IAQ index results of various environmental characteristics

θ_2	Above Ground	Lobby	Food and beverage	Back of house	Supermarket	Cosmetic	Near toilet
<0.32	325	252	784	539	610	539	365
0.32-0.42	3718	10	3643	1289	784	852	1078
0.43-0.53	6928	0	6904	1832	1017	1192	722
0.54-0.64	1188	0	1798	155	716	144	11
>=0.65	579	0	1523	809	137	809	0
Fail ratio	0.14	0.00	0.23	0.21	0.26	0.27	0.01
	Basement	Not lobby	Not Food and beverage	Not Back of house	Not supermarket	Not Cosmetic	Not near toilet
<0.32	419	492	325	570	499	570	744
0.32-0.42	817	4062	1070	3424	3929	3861	3635
0.43-0.53	2126	8973	2151	7223	8038	7863	8333
0.54-0.64	860	2048	250	1893	1332	1904	2037
>=0.65	946	1525	2	716	1388	716	1525
Fail ratio	0.35	0.21	0.07	0.19	0.18	0.18	0.22

6.5. Summary

Traditional objective-criteria IAQ assessment method measures and compares a number of IAQ parameters listed in standards and health criteria. It usually requires massive material and manpower resources. The daunting assessment process and use of numerous bulky equipment become nuisances to occupants and building owners, making IAQ assessment less popularized. Over the years, IAQ concerns have increased drastically especially when it is related to health risks. Nevertheless, despite the efforts of the development of IAQ index that can screen out problematic IAQ premises without conducting a full IAQ assessment, neither the government nor the industry has taken a step forward to embrace the new form of IAQ assessment and monitoring method.

IAQ index has been proven to be a handy screening tool to identify indoor environments with high chance of poor IAQ that require further comprehensive IAQ assessments, and those with lower chance of problematic IAQ can be maintained, therefore saving resources by prioritizing IAQ improvements. In this chapter, based on the theory and methodology of IAQ index, different combinations of dominant IAQ parameters are adopted in a step-wise IAQ screening protocol to facilitate cost-effective IAQ management. IAQ index θ_1 with CO_2 alone, IAQ index θ_2 with CO_2 and PM_{10} and IAQ index θ_3 with CO_2, PM_{10} and TVOC are proposed and their performance for identifying undesirable IAQ are evaluated. In general, by assuming a pre-test probability of one rank higher than the actual failure probability by full test, the screening results will be of one rank higher than the full test results. If a compatible pre-test probability is assumed, the screening test will give results similar to full test results. Screening using IAQ index θ_1

give a low-resolution assessment with only two to three out of six VPEs, being able to identify only a small group of IAQ data with low chance of poor IAQ. Higher assessment resolutions are resulted by screening with IAQ indices θ_2 and θ_3, involving three to four categories out of six. θ_2 and θ_3 are able to screen out not only low but also high-risk group of having unsatisfied IAQ.

Further to this, a step-wise IAQ screening protocol is proposed by screening the IAQ data consecutively using different IAQ index combinations. It is again demonstrated that a high estimate on the pre-test failure probability will result in an overestimation of failure probability by similar degree. Given a predetermined threshold based on resource and health considerations, results suggest that all screening strategies can successfully reduce the number of premises required to undergo a full IAQ assessment. It can be seen that IAQ screening strategies can assist the identification of undesirable IAQ with engineering acceptable accuracy, at the same time screen out those do not require attention. IAQ screening strategies are simple and economical for IAQ monitoring and mitigation, therefore will be beneficial for large-scale IAQ screening to evaluate the overall IAQ situation in the region.

Since current IAQ measurement methods cannot identify IAQ problems instantaneously, building occupants are usually prone to IAQ-related sicknesses and diseases. With technological advancement, long-term IAQ surveillance becomes feasible and economical. In order to demonstrate and evaluate the feasibility of using low-cost IAQ sensors to monitor and screen out problematic IAQ, a large-scale IoT-based IAQ screening is conducted in a multifunctional shopping mall to collect spatial and temporal IAQ information.

By looking at the 3-month IAQ data collected by 80 IAQ sensing modules installed in various locations of the mall, IAQ problems were discovered, which include high TVOC levels in majority of sampling locations, especially in basement, food and beverage area and back of house area, which could be attributed to environmental factors like location, function of the area, activities of the area, etc. High PM_{10} are observed on basement and lower floor of the mall, mainly in food and beverage area and back of house corridor. IAQ index with 2 parameters can successfully identify the environmental characteristics with higher chance of poor IAQ.

All things considered, this chapter proposes and evaluates the feasibility of IAQ screening strategies and the use of IoT-based low-cost IAQ screening system for large-scale IAQ monitoring. Although they are highly dependent on the surrogate parameters selected, they are proven to be useful for identifying problematic IAQ, sources of problems and high-risk factors, with lower cost and resource requirement. The proposed assessment methods shall facilitate IAQ management in indoor environments.

Chapter 7. Conclusion

IEQ is a complex issue with numerous physical, subjective and contextual influencing factors. Interconnection, interdependency and prioritization of IEQ factors have been observed, making it difficult to assess an environment in terms of the provision of a healthy, comfortable and productive space.

This thesis identifies the inadequacy of current IEQ, thermal comfort and IAQ assessment methods and model, and develops novel assessment approaches to evaluate building performance and accurately predict occupant's satisfaction to perceived environment.

Overall indoor environmental quality (IEQ) and thermal comfort

IEQ responses from very small residential units are investigated, discussed and compared to already establish subjective-objective belief in average residential buildings, revealing the inadequacy of IEQ regression models of not able to give accurate predictions if occupants have developed their own perceptions and/ or adaptions towards the environment. Moreover, sleeping thermal comfort survey demonstrates the needs for different task-specific comfort requirements. Consistent and unified building comfort conditions may not be suitable for all settings. Given no currently available model for every environmental setting, thermal comfort and IEQ models shall be able to update based on newly acquired subjective responses by occupants in the field.

In fact, as many have observed certain degree of performance gap in existing comfort prediction models, which can lead to errors and uncertainties in research and practical purposes. It has come to concern that prediction models that look for the deterministic causal relationships between environmental quantities and occupant's comfort may not be able to fully reflect one's opinions on perceived environments. Discrepancies can be caused by limited number of factors being used in model development, descriptive contextual factors that cannot be expressed in quantity, insufficient sample size, bias in modelling dataset, adaption and tolerance, etc.

Undoubtedly, subjective evaluation is the most effective way to identify occupant's responses and acceptance towards the environmental conditions. It is able to overcome the above-mentioned limitations of existing models by examining occupant's mental state, perceptions, feelings and emotions. It is however lacking universal judgement and practical implication of improving the IEQ, health and energy usage (Asadi, Mahyuddin et al., 2017). It is therefore essential to establish linkage between subjective assessment results with objective environmental conditions. However, given the complex relationship between IEQ factors discovered by previous research efforts, IEQ responses have been proven to be influenced by numerous features including environmental factors, functional factors (task-related) and psychological influences (occupant-related), and with the possibility of developing tolerance and adaptation, the linkages between all these factors and IEQ responses may change over time. IEQ modelling cannot be fully expressed in a reductive physical manner of causal relationship between environmental quantities and occupant's responses.

In view of the limitations, an open probabilistic acceptance model using frequency distribution function is developed to handle diverse range of descriptive IEQ parameters in addition to the four major numerical factors forming the argument of environmental quality. It makes model updating easier and is more robust in reflecting occupant's environmental perception. Nevertheless, the characteristics of data used strongly affect the accuracy, relevance and applicability of any model (Heinzerling, Schiavon et al., 2013). The best approach would be to incorporate the statistical significance of subjective responses by occupants into acceptance prediction models such that the relationship between environmental quantities and occupant's responses is updated with the influence of contextual factors and perceptions.

To this end, Bayesian updating protocols for thermal comfort and overall IEQ model are developed and demonstrated. It is understood that the sample size in model and protocol development may be too small for establishing the validity. This thesis aims at providing a methodology, a framework, or a strategy for addressing the problem exist in current IEQ modelling. The intention is not to proposed an updated model for IEQ prediction, but to demonstrate the proposed modelling method using existing data as an example. Bayesian approach allows systematic updates of current thermal comfort and IEQ beliefs (i.e. acceptance prediction models) with openly available field data. This approach incorporates field settings into any existing model by considering the statistical significance of field data, even with a small sample size. Presented with practical examples of existing thermal comfort model and IEQ regression model with the best information available, the proposed Bayesian updating procedure can be useful for indoor environmental management with a selection of target sample size and acceptable error based on managerial decision. It provides an achievable solution to the present challenges in establishing a reliable environmental acceptance prediction model.

Indoor air quality (IAQ)

Due to the adverse health effects seen with poor IAQ, including acute physical symptoms induced by exposure to high levels of air pollutants, and the development of long-term sicknesses caused by accumulative exposure to low to medium levels of pollutants, IAQ assessment cannot solely rely on subjective sense, and shall also be evaluated objectively against health standards. In fact, standardized protocols for IAQ assessments have been developed. However, these protocols require sophisticated instruments operated by professionals. It is expensive, and cannot identify IAQ problems instantaneously. In the absence of continuous IAQ monitoring, building occupants are exposed to the risks of poor IAQ without noticing.

In view of this, this thesis proposes a step-wise IAQ screening protocol using different IAQ index combinations. With a predetermined threshold based on resource and health considerations, IAQ screening strategies reduce the need for conducting full IAQ assessment. IAQ screening protocol can identify undesirable IAQ with engineering acceptable accuracy and screen out those do not require attentions. Measuring only few parameters, IAQ screening strategies are simple and economical for IAQ monitoring and mitigation, which is beneficial for large-scale IAQ screening.

In addition to developing IAQ screening protocol for simple and fast IAQ evaluations, this thesis also demonstrates and evaluates the feasibility of using low-cost IAQ sensors to monitor and screen out problematic IAQ. A large-scale IoT-based IAQ screening is conducted in a multifunctional shopping mall to collect spatial and temporal IAQ information. IAQ index successfully identified the environmental characteristics that contributes to poor IAQ.

To sum, IAQ screening protocol and IoT-based IAQ screening practice are useful for preliminary identification of problematic IAQ, sources of problems and high-risk factors, with substantially lower cost and resource requirements compared to traditional IAQ assessment methods. The proposed novel approaches for IAQ evaluation and monitoring shall facilitate IAQ management in indoor environments.

Perspective on future research direction

This thesis reveals huge research potential for environmental acceptance modelling. Development of holistic subjective-objective prediction models with comprehensive parameters was limited due to the constraints of field data acquisition in the past. With scientific research and development of big data collection, extraction and analysis in recent year, large volume of various forms of IEQ data can be gathered at an unprecedented speed. IoT-based and wireless low-cost sensors, as demonstrated, provide an alternative method for data collection and a new perspective of data management and exploration. Measurements of environmental quantities and surveys of responses and acceptance, in foreseeable future, will be at a much lower cost and a faster speed compared to at present. Data acquired, even though may not be as precise as those collected using expensive instruments, will allow us to gain spatial and temporal understandings of the environmental conditions. With such all-inclusive data, IEQ prediction models that can encapsulate and express all IEQ influencing factors will be possible.

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