Longitudinal assessment of thermal and perceived air quality acceptability in relation to temperature, humidity, and CO_2 exposure in Singapore

Toby C.T. Cheung[1*], Stefano Schiavon[2], Elliott T. Gall[1,3], Ming Jin[4], William W Nazaroff[5]

[1] Berkeley Education Alliance for Research in Singapore, Singapore

[2] Center for the Built Environment, University of California, Berkeley, California, USA

[3] Mechanical and Materials Engineering, Portland State University, Portland, USA

[4] Electrical Engineering and Computer Sciences Department, University of California, Berkeley, California, USA

[5] Civil and Environmental Engineering Department, University of California, Berkeley, California, USA

Corresponding email: toby.cheung@bears-berkeley.sg

Abstract

Thermal acceptability (TA) and perceived air quality acceptability (PAQA) are typically analysed in climate chambers or cross-sectional field studies. Individual factors, such as expectations and perceived environment history, may influence the acceptability response. Longitudinal studies with multi-day design are absent in the literature. Fifteen Singaporean subjects participated in a 7-day longitudinal experiment in which they carried a portable sensor that continuously recorded personal air temperature, relative humidity and carbon dioxide concentration at 1-minute intervals. Instantaneous TA and PAQA were regularly sampled by survey for each subject.

High acceptability was found at home, restaurants and workplaces, whereas low acceptability was found for outdoor and transport environments. The participants from Singapore's modern tropical environment spent an average of 96% of their time indoors. Weak associations were reported between acceptabilities and measured physical parameters taken independently. Clustering data by location, subject's sleeping ventilation habit, air-conditioning operation status and the changes in physical parameters over a designated time period enhanced the understanding of the acceptability results. In general, acceptability was lower for those who slept in air-conditioned environments than for those who slept without air-conditioning. The carbon dioxide mixing ratio was critical for PAQA predictions but not for TA. The Gaussian process (GP) had a better predictive power than a multiple linear regression approach. Using GP, we found that a general predictive model had comparable simulation performance as for individual predictive models. The longitudinal experiment has demonstrated effectiveness for TA and PAQA analysis, which could be beneficial to future studies in personal comfort prediction.

Keywords: Environmental exposure history, Perceived air quality acceptability (PAQA), Personal acceptabilities simulation, Thermal acceptability (TA), Wearable sensor

1 Introduction

Satisfactory thermal and perceived air quality of the indoor environment is one of the central goals of building design and operation. Evidence in the literature indicates that thermal acceptability (TA) may affect occupant performance [1–5], and perceived air quality acceptability (PAQA) is found to be associated with a number of sick building syndrome (SBS) symptoms [6-9].

Most thermal comfort and perceived air quality studies have been conducted in controlled environmental chambers [10,11] or using cross-sectional field surveys focusing on specific environments, such as offices [12–14], residences [15,16], and classrooms [17–19]. Some studies have extended the measurement protocol to a partial longitudinal approach, evaluating acceptability over longer periods and including the monitoring of environmental parameters, such as air temperature, relative humidity, and carbon dioxide concentration, but always at a fixed location, for example in an office or a bedroom [20,21].

Beyond the physical and physiological attributes, personal assessment of environmental acceptability can also be psychologically affected by a subject's expectations, environmental context, the availability of environmental control, and the thermal and perceived air quality history of the subjects [2,22–24]. For example, Chun *et al*. [22] studied the effect of measured thermal history (24 h) on thermal sensation when subjects were exposed to similar conditions in a climatic chamber. This study found that subjects exposed to higher daily temperatures tended to respond with 'cooler' thermal sensations than subjects with lower daily temperature exposures. They also found that occupants who used air-conditioning at home were more sensitive than those who did not. Lower thermal acceptability was reported in a field study if occupants were previously exposed to air-conditioned spaces [25] and the presence of air conditioning may lead to narrower range of conditions for thermal acceptability [26]. Fang *et al*. [27] have suggested that a short-term increase of temperature and humidity would reduce a subject's evaluation of perceived air quality as acceptable.

Existing prediction tools for thermal or perceived air quality satisfaction are either designed for specific spaces or lack the ability to include subject's environment exposure characteristics, history and expectations [28–31].

We performed an experiment in which fifteen subjects carried, for seven days each, a portable sensor that continuously measured and recorded their local air temperature (T_a), relative humidity (RH) and carbon dioxide concentration (CO_2). Detailed information about the experimental design and results for carbon dioxide exposures were previously reported [32]. Here, we focus on the instantaneous assessments by participants of the thermal and perceived air quality acceptability of the spaces they occupied. Several factors may affect acceptability beside air temperature, humidity, and CO_2. We analyzed the influence on acceptability of short-term changes in the physical environmental parameters, subject's daily temperature, humidity and CO_2 exposure, locations (home, outdoor, restaurant, transport, workplace), presence of air conditioning and occupant's sleeping ventilation habits at home. The advantages of a longitudinal design include the ability to trace the history of individual exposure to environmental parameters and the possibility to study the influence of personal expectations in various environments, which is a novel step towards identifying important confounding factors that influence a subject's TA and PAQA responses.

The objectives of this study are (i) to identify if location, use of air conditioner when sleeping, air conditioning status, and thermal and air quality history influence thermal and perceived air quality acceptability (TA and PAQA), and (ii) to assess from among several alternatives which parameters and simulation algorithms effectively predict TA and PAQA.

2 Methods

2.1 Subjects

Fifteen subjects, who were students and professional/office workers living in Singapore, participated in this study. The participants' demographic attributes and air-conditioner usage habits at home were collected, including age, sex, body height and weight, number of air-conditioner units at home and their sleeping ventilation (SV) status. With

respect to sleeping ventilation, subjects were categorized as sleeping in an air-conditioned bedroom (AC group) or in a naturally ventilated bedroom with window open (NV group), while those who experienced both ventilation practices during the monitored period are classified into a mixed (MX) group. The thermal environment for sleeping reflects a high degree of autonomous choice, which can potentially reflect an individual's preferred status for ventilation and thermal environmental control. It is also noted that the "AC group" classification refers to participants who slept in an air-conditioned bedroom; it does not necessarily imply that the AC group participants continuously operate their air-conditioner at home.

2.2 Physical measurements

Each participant carried a portable sensor, which continuously recorded air temperature (°C), relative humidity (%) and carbon dioxide mixing ratio (ppm) at 1-minute intervals, for seven consecutive days. In case of sensor failure, participants were encouraged to extend their participation to realize a cumulative seven-day log; the result was a discontinuous record for some participants. The subjects were instructed that the sensor should be carried or kept near the participant at all times during the measurement period. The real-time continuous measurement revealed information about environmental conditions in relation to the participant's activity patterns and their exposure to environment parameters. The chosen data logger was CM-0018 (CO2Meter Inc., Ormond Beach, FL, USA) with manufacturer-reported sensor accuracy being the greater of ±30 ppm or ±3% of the measured value for CO_2, ±0.4 °C for air temperature and ±3% for relative humidity [33]. The results presented in this study were rounded to the nearest 0.1 °C, 1%, and 10 ppm.

2.3 Subjective acceptability survey

An online survey was developed and utilized to elicit and record each subject's instantaneous evaluation of thermal acceptability (TA) and perceived air quality acceptability (PAQA). The subjects used their smartphone to respond to the survey throughout each day. A response was requested after each environment change (i.e., considering home, outdoor, transit, and office environments). However, the thoroughness of the response rate was constrained by each participant's availability and willingness to record their responses. Subjects' TA and PAQA responses include both the first exposure on changing environments and a habituated assessment at the same location. The subject marked their acceptability response on a continuous scale from clearly acceptable (+1) to just acceptable (+0.01) and from just unacceptable (-0.01) to clearly unacceptable (-1). The gap between just acceptable and just unacceptable requires subjects to distinguish between acceptable and unacceptable without a neutral choice. Results of the subjective survey are subsequently analyzed in two ways: 1) thermal and perceived air quality acceptability (TA and PAQA) as a continuous scale within the ranges noted above and 2) thermally and perceived air quality acceptable/unacceptable vote indicating a dichotomous scale either "Acceptable" or "Unacceptable" response based on a positive or negative sign from the response on the continuous scale.

2.4 Activity schedule record

Participants were also asked to record their daily activity schedule and the characteristics of each perceived environment during the measurement period, including the time of entry in each place, their activity (walking, sleeping, working, etc.), air-conditioning status (on or off) and a description of the type of location (including home, workplace, outdoor, restaurant and transport; places not in these categories were classified as 'other' and

were to be specified by the participant in a remark section). None of the participants had a private car and so the category "transport" would generally mean public transportation such as metro (light rail), taxi or bus. In Singapore, these transport spaces are consistently air-conditioned.

2.5 Statistical analysis

A local polynomial non-parametric regression fitting method, the 'loess' function in R programming, was applied to visualize the non-linear association between the evaluated acceptabilities (TA and PAQA) and potential predictor variables. The non-parametric Wilcoxon rank sum test, also known as the Mann-Whitney test, was used to assess the effect of categorical variables on acceptability. For all tests, the results were considered statistically significant when $p < 0.05$. The statistical analysis was carried out using R software version 3.2.3 [34].

To predict TA and PAQA, two approaches were used: (i) multivariable linear regression (MLR); and (ii) a machine-supervised learning algorithm named Gaussian process [35] ('gausspr' functions in the R programming software). Linear regression allows direct interpretation between predictors and outputs. The Gaussian process is a non-parametric model benefit for small dataset and it allows precise trade-off between fitting data and smoothing, but the relationships between inputs and outputs cannot be explicitly interpreted. One of the key advantages of the Gaussian process is that it does not require a prior assumption about the specific functional form (e.g., linear or logarithmic) for the relationship between the independent and dependent variables.

Different combinations of potential predictor variables were used in the acceptability prediction model tests. Model performance was quantified by the coefficient of determination (r^2), mean square error (MSE) and mean absolute error (MAE) between the surveyed and predicted acceptabilities. The calculated r^2 is a number that identifies the proportion of variance in the dependent variable that is predictable from the independent variable (expressed in Equation 1). MSE is a risk function to assess the quality of predictor by comparing the difference between observed "O" and predicted "P" values (expressed in Equation 2). MAE is a more robust measure of the average magnitude of prediction difference without considering the error's direction (expressed in Equation 3). A 500-fold cross-validation was applied in each test, randomly partitioning the data into two sets of 70% for training and 30% for validation, and repeating the training and validation process 500 times. The estimators (r^2, MSE and MAE) were averaged over the 500 runs to enhance model stability [36,37]. A good simulation model is justified by smaller values of MSE and MAE along with a higher r^2 value.

$$r^2 = 1 - \frac{\sum_i (P_i - \acute{O})^2}{\sum_i (O_i - \acute{O})^2} \tag{1}$$

$$MSE = \frac{1}{n} \sum_{1=1}^{n} (P_i - O_i)^2 \tag{2}$$

$$MAE = \frac{1}{n} \sum_{1=1}^{n} |P_i - O_i| \tag{3}$$

3 Results and Discussion

3.1 Measurement results

Table 1 shows the overall results of measured parameters and surveyed acceptability (TA and PAQA) classified among five different categories of locations. Measurement samples at locations not described by the five categories are excluded because of limited data. The cumulative data count suggested that participants' time-location budget was apportioned on average as follows: home (61%), workplace (26%), outdoor (4%), restaurant (4%), transport (3%), and other (2%). On average, 96% of subjects' time was spent indoors.

Table 1. Overview of measured and surveyed data in different environments. [a]

Percentile	Home (N = 90963)			Outdoor (N = 6610)			Restaurant (N = 6095)			Transport (N = 4938)			Workplace (N = 38384)		
	T_a	RH	CO_2	T_a	RH	CO_2	T_a	RH	CO_2	T_a	RH	CO_2	T_a	RH	CO_2
10%	26.2	56	430	26.4	59	410	24.4	53	410	26.0	43	450	24.1	47	410
25%	27.9	61	510	28.1	65	420	26.3	56	450	27.1	49	760	25.1	53	450
50%	29.7	65	720	29.7	70	470	27.5	60	590	28.4	55	1330	26.0	56	510
75%	30.9	70	1070	31.0	75	550	29.9	67	780	29.8	62	2150	26.8	60	600
90%	31.6	74	1520	31.8	81	740	31.4	71	1250	30.9	71	3050	27.7	90	870
Number of surveyed acceptable / unacceptable choice [b]															
Thermally Accept.	115 (82%)			9 (50%)			39 (85%)			83 (55%)			159 (83%)		
Thermally Unaccept.	26 (18%)			9 (50%)			7 (15%)			69 (45%)			32 (17%)		
PAQ Accept.	118 (84%)			13 (76%)			37 (82%)			55 (36%)			173 (91%)		
PAQ Unaccept.	22 (16%)			4 (24%)			8 (18%)			97 (64%)			18 (9%)		

[a] Symbols (units): T_a = air temperature (°C); RH = relative humidity (%); CO_2 = carbon dioxide mixing ratio (ppm); N = number of measurements in indicated microenvironment; sampling time resolution = 1 min.
[b] Aggregate number (percentage) of responses for thermally and perceived air quality (PAQ) acceptable (0.01 to 1) / unacceptable (-0.01 to -1) choices at the indicated location.

Consistent with its tropical location, outdoor environmental conditions in Singapore were consistently warm (10th percentile, median, 90th percentile of T_a = 26.4, 29.7, 31.8 °C) and humid (RH = 59%, 70%, 81%). About two-thirds of the samples acquired at home were not air-conditioned and the corresponding physical parameters (28.2, 30.6, 31.7 °C; 62%, 69%, 75%) were comparable to the outdoor values. The surveyed residences, especially for those public housing units constructed by the Housing Development Board, were only equipped with air-conditioning in the bedrooms; other parts of these apartments are typically served by naturally ventilation. In the air-conditioned bedrooms, the temperature (24.8, 27.8, 30.2 °C) and relative humidity (52, 61, 67%) were, on average, 2.6 °C and 9% lower, respectively, than the residential spaces that were not air-conditioned. The carbon dioxide mixing ratio at home with AC on was considerably higher (560, 1000, 2230 ppm) than in the cases without air-conditioning (410, 570, 1260 ppm). Similarly, the restaurant environment included both AC (N = 3623) and non-AC (N = 2472) samples. Likewise, sampled temperature (23.1, 25.0, 29.9 °C), relative humidity (52%, 59%, 70%) and CO_2 level (500, 710, 1430 ppm) at AC restaurants were lower, lower, and higher, respectively, than at the non-AC restaurants (26.4, 29.8, 32.1 °C; 54%, 63%, 73%; and 390, 440, 670 ppm). Overall, in the non-AC restaurants, average temperature and humidity were 2.8 °C and 3.1% higher but CO_2 levels were 330 ppm lower than in the AC restaurants. All samples from workplace and transport environments were air-conditioned. The temperatures and CO_2 mixing ratios in

workplace were 24.1, 26.0, 27.7 °C and 410, 510, 870 ppm respectively. In transport, the sampled humidity (43%, 55%, 71%) was found to be comparable with the workplace; however, higher temperatures (26.0, 28.4, 30.9 °C) and CO_2 mixing ratios (450, 1330, 3050 ppm) were recorded. The 90th percentile level of CO_2 in transport environments is particularly striking; it is likely associated with a generally high occupant density especially during commute times on buses and in the rail mass rapid transit system (MRT). A detailed analysis of the CO_2 levels encountered and their potential significance has been reported by Gall et al. [32]. Table 1 also summarizes the surveyed subjects' assessment of thermal and perceived air quality acceptable/unacceptable choice. The thermal environment and perceived air quality were found to be acceptable for more than 80% of responses at all locations, except for outdoor (proportion of respondents' acceptable choices were 50% for thermal environment and 76% for air quality) and in transport (thermal environment: 55%, air quality: 36%).

Figure 1 presents a boxplot of TA and PAQA assessments in the five different location categories. Higher thermal acceptability was found in workplaces, restaurants and at home, respectively, with median values of 0.34, 0.38 and 0.51. A lower median TA was observed in transport (0.02) and half of the outdoor TA votes were "unacceptable" with a median value of 0.03. A higher thermal acceptability at home, when a similar warm temperature is recorded as outdoors, might be related to the lack of direct solar radiation, other radiant heat transfer effects, subjects' metabolic rate (likely systematically higher when outdoors than when at home), and subjects' behavioral adjustments such as operating a fan and wearing less clothing. Being thermally dissatisfied outdoors is an expected outcome in Singapore with its warm and humid climate. A lower TA satisfaction rate in transport could be explained by relatively high temperature (compared to workplaces, for example) and other factors such as close proximity among occupants, especially during peak travel times [38]. For perceived air quality acceptability, high median PAQA value was observed at home (0.59), at the workplace (0.58), in restaurants (0.55) and outdoors (0.46); a much lower median PAQA (-0.22) was reported in transport. The high CO_2 mixing ratio in transport (10th percentile, median, 90th percentile = 450, 1330, 3050 ppm) could be one contributor to unacceptable air quality, but this interpretation may not equivalently hold when applied to other locations. For example, no unacceptable votes for perceived air quality were recorded at home when the air-conditioning was turned on with high CO_2 mixing ratio (560, 1000, 2230 ppm).
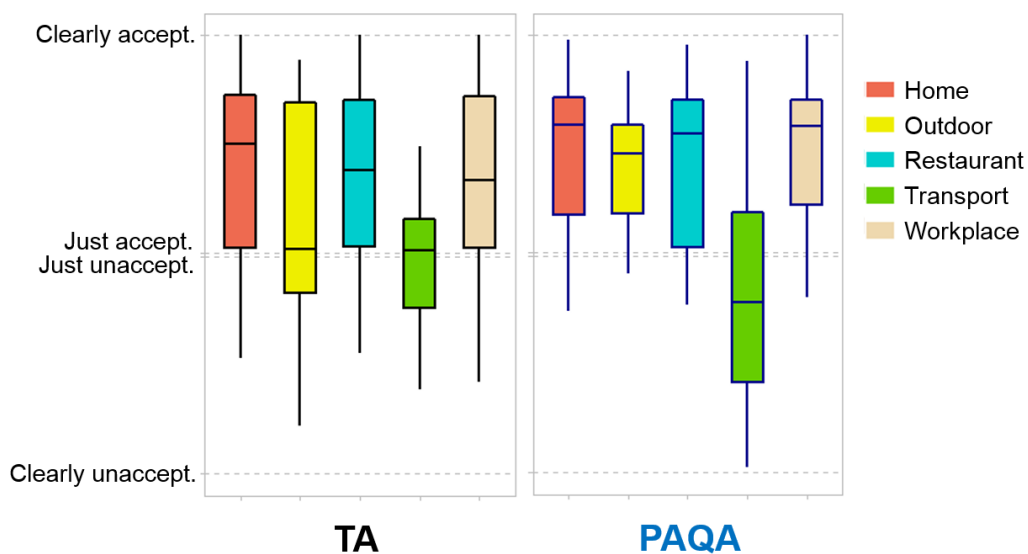
Figure 1. Overview of subject's assessments of thermal acceptability (TA) and perceived air quality acceptability (PAQA) in various places. In each box, the central mark is the median, the edges denote 25th and 75th percentiles, and whiskers extend to ±1.5 times the inter-quartile range.

3.2 Individual differences in exposure and acceptability

Figure 2 shows temperature, relative humidity, CO_2 mixing ratio, TA, PAQA and the percentage of time spent in recorded locations for each participant. The number of each individual's effective monitoring days and thermal and perceived air quality acceptable votes are summarized in the supporting information (Table S1). Each participant was assigned a reference name, from left to right, associated with their sleeping ventilation status (AC, NV or MX), sex (M or F) and a reference number. The personal daily average temperature, relative humidity and CO_2 exposure were plotted in Figure 2 using a red dot, which is determined by averaging the physical parameter values for each monitoring day of the survey period. The evidence presented in this figure illustrates that personal exposure to the monitored parameters, time spent in each location, and acceptability responses can be significantly different. This observation is not surprising since living style and environmental exposure patterns are distinct among individuals, as would be their subjective satisfaction with the environments they inhabit.
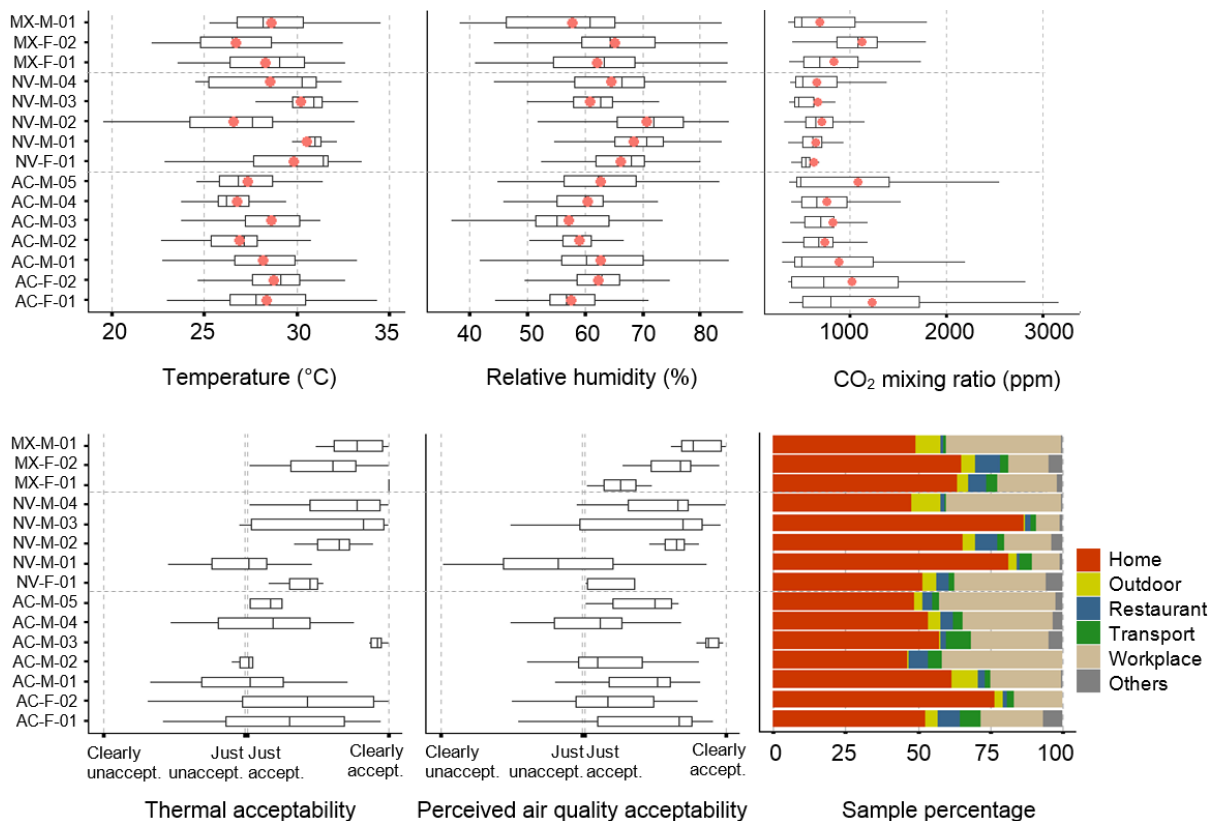

Figure 2. Individual distributions of temperature, relative humidity, CO_2 mixing ratio, thermal acceptability, perceived air quality acceptability and sample locations. Statistical meanings for box and whiskers are the same as marked in Fig 1. The red dot in each box represents the individual's average daily environmental exposure to temperature, humidity and CO_2 level.

The AC group who slept with air-conditioning operating tended to be exposed to lower air temperatures and relative humidities, but higher CO_2 levels than the NV group, since most of the participants spent 50% or more of their time at home. In addition, average daily CO_2 exposure for the AC group was substantially higher than the recorded median CO_2 mixing ratio during the experiment; the likely explanation is that the highest home CO_2 levels for the AC group occurred while sleeping [32]. Regarding acceptability responses, the MX group was observed to record higher TA and PAQA than the other two groups. In general, the NV group recorded higher thermal acceptability than did the AC group. Two exceptions were subjects "NV-M-01" and "AC-M-03." A majority of surveyed acceptability ratings by "NV-M-01" occurred in the transport environment (with lower satisfaction rate); acceptability votes by "AC-M-03" were dominated at home and workplace (with higher satisfaction rate).

Figure S1 in the supporting information presents the Figure 1 data reassessed with the exclusion of "NV-M-01." This adjustment increased the median TA and PAQA in transport from 0.02 to 0.27 and from -0.22 to 0.54 (p<0.01); the percentage of thermal and perceived air quality acceptable votes in transport was improved from 55% to 74% and from 36% to 72%, respectively.

3.3 General relationships between environmental parameters and acceptability

Figure 3 illustrates the relationships between the surveyed subject's acceptability assessments (TA, PAQA) and measured environmental parameters (temperature, humidity, and CO_2 level). The sample data from "NV-M-01" is excluded to avoid biased interpretation from a single subject where nearly all assessments occurred in a single location category. Strong relationships between acceptability (both TA and PAQA) and the measured environmental parameters were not observed in the tested conditions. The weighted-regression lines suggest generally acceptable conditions within the sampled temperature and relative humidity ranges (22.5–32.5 °C and 40–80%). A dome shaped trend was found between TA and temperature, where the highest weighted TA (0.49) was observed when temperature was 27.8 °C. It makes sense that thermal acceptability would decline when subjects are exposed to environments that are either too warm or too cool. However, as can be observed in Figure 3, thermal acceptability was widely dispersed over the spectrum of acceptability responses at 27.8 °C, and it appears that further environmental and personal information would be needed to improve predictability. Evidence in Figures 2 and 3 demonstrates that relationships were not robust between acceptabilities (especially TA) and the measured parameters alone. Some clustering of the data such as environment locations, air-conditioning operation status and sleeping ventilation groups could be valuable in clarifying the relationships between acceptabilities and the physical parameters.
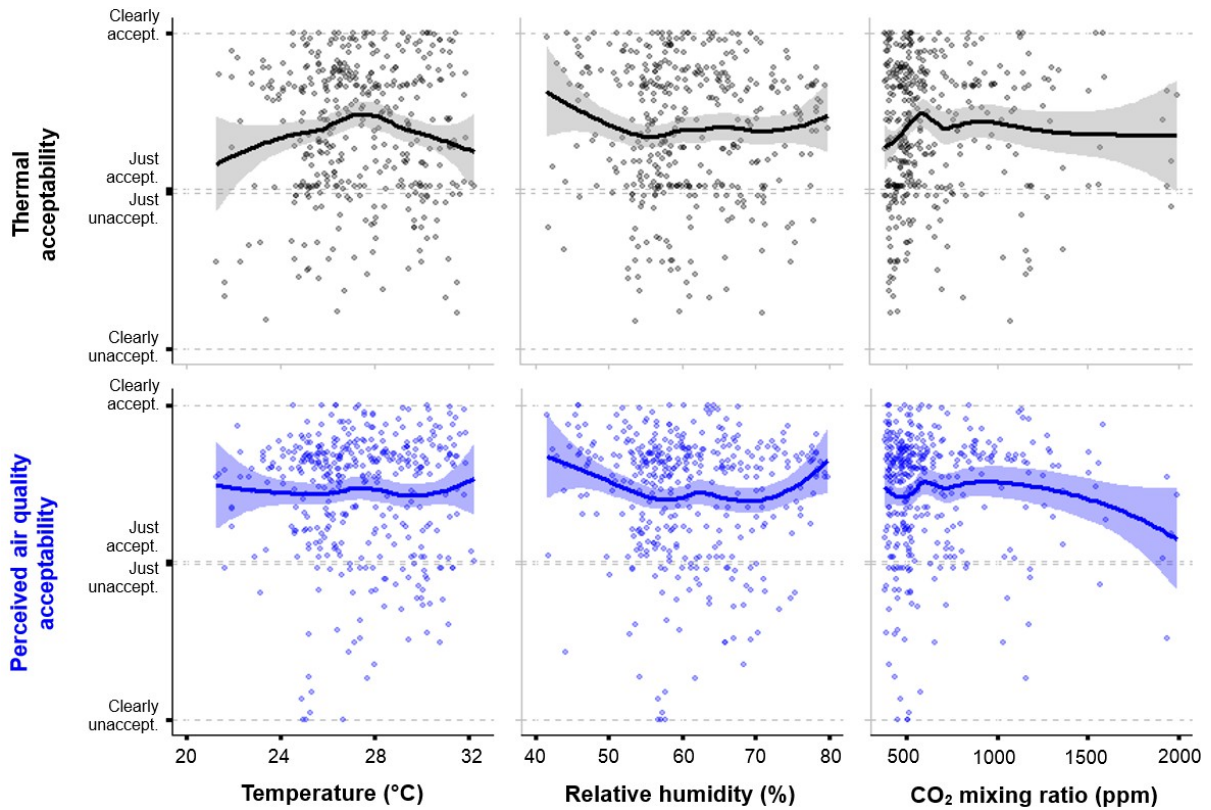
Figure 3. Overall relationships between assessed acceptabilities (TA, PAQA) and environmental parameters (T_a, RH, CO_2). The regression line was fitted locally by weighted least squares and 95% confidence intervals are shown as shaded areas in the plots.

3.4 Influence of location and sleeping ventilation on acceptability responses

Figure 4 illustrates the relationships between (i) TA and air temperature, and (ii) PAQA and CO_2 mixing ratio when data are clustered by location and by the subject's sleeping ventilation habits (and excluding subject "NV-M-01"). The outdoor environment is excluded owing to insufficient data, and the MX sleeping ventilation group is also removed for simpler visualization.

Overall, the data suggest that lower thermal acceptability was associated with higher air temperature at home, when the air-conditioner was likely turned off. However, in air-conditioned transport and workplace environments, the data suggest that lower temperatures did not necessarily correlate with improved thermal acceptability. The percentage of subject ratings of thermally acceptable vote was less than 80% when temperature was lower than 25 °C in the workplace. The workplace temperature corresponding to the highest thermal acceptability for both AC and NV groups was found to be 25.8 °C. Since the typical set-point in commercial buildings in Singapore is reported to be 23 °C [39], and the annual mean outdoor air temperature during the hours 7 AM to 7 PM in Singapore is 29 °C, with little seasonal variation [40], large energy savings could be realized by raising the indoor temperature set-point to 26 °C [40,41]. The findings here imply that energy savings of an increased temperature set point may be accompanied by improved thermal comfort in Singapore workplace environments. Dissatisfaction regarding overcooled working environments has been previously reported for Singapore offices [42,43]. Yet, such conditions were not common in our surveyed database, for which the median recorded

workplace temperature was 26 °C (Table 1). In the transport location category, the thermally acceptable choice declined to below 60% when temperature was below 25 °C or above 31 °C.

Further analysis of the sleeping ventilation groups showed lower median TA for the AC sleeping group as compared to the NV sleeping group at restaurants (Wilcoxon test, $p<0.001$), in transport ($p=0.002$) and in workplace ($p<0.001$) environments, while the difference found at home ($p=0.42$) was statistically insignificant. In workplaces and in other environments where personal environmental control is not available, subjects who sleep with air-conditioning reported less satisfaction with TA and PAQA than those who sleep without air-conditioning. These results are aligned with the findings of Chun *et al*. [22]. It may be that the AC group was accustomed to controlling their sleeping environment, and may have higher expectation than the NV group in environments with individually uncontrollable ventilation and thermal conditions. Another reason could be a dependency ("addiction") of those accustomed to air conditioning while sleeping to a higher level of thermal control for the other environments that they occupy [44].

A high percentage of responses reported that air quality was acceptable both at home (84%) and in workplaces (91%) for both the AC and NV groups. No clear relationship between PAQA and CO_2 mixing ratio is observed. Similarly, an association between PAQA and CO_2 mixing ratio was not found in restaurants; however, a higher median PAQA was found for the NV group in this setting as compared with the AC group ($p=0.008$). A speculative explanation is that the AC group might be adversely sensitive to the restaurant environment especially without air conditioning, when the conditions are warm (26.4, 29.8, 32.1 °C) and humid (54%, 63%, 73%), whereas the NV group, with lower expectations for environmental control, found the thermal and perceived air quality conditions to be more acceptable in restaurants regardless of air-conditioning status.

In the case of transport environments, lower median PAQA was reported by the AC group ($p=0.09$) as compared to the NV group and no clear trend was found between PAQA and CO_2 mixing ratio. Although the CO_2 mixing ratio did not assist in visualizing a trend in PAQA, it was found to be an important predictor variable for PAQA simulations using the Gaussian process (see §4).
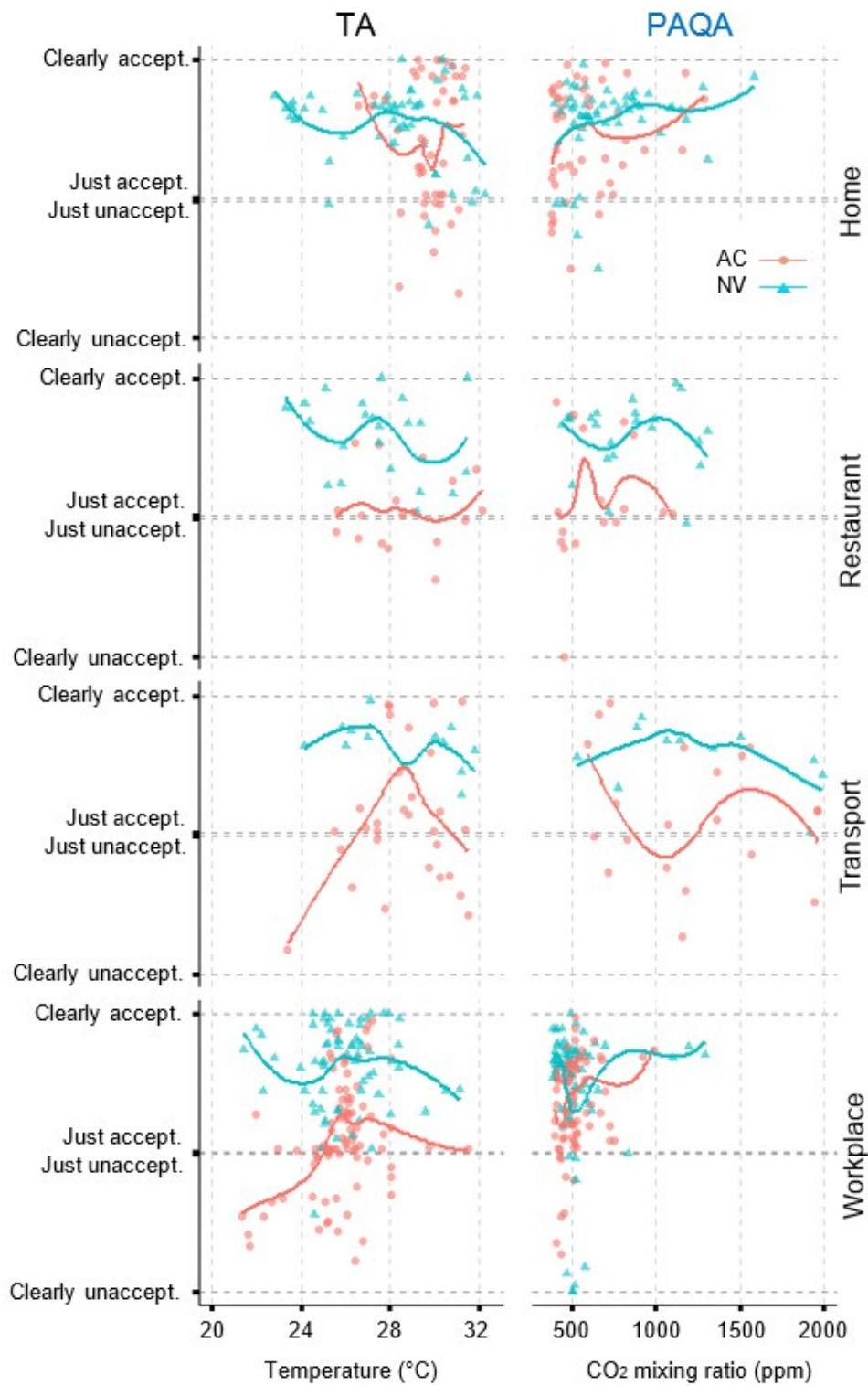
Figure 4. Relationships between (left frames) thermal acceptability (TA) and temperature and (right frames) perceived air quality acceptability (PAQA) and CO_2 mixing ratio. Responses are classified according to location of the response and the sleeping environmental condition (air conditioned [AC] versus naturally ventilated [NV]) of the subjects.

3.5. Thermal and air quality history

In exploring the factors that could potentially influence rated thermal and perceived air quality acceptabilities, we considered the recent history of exposure as a factor. In specific analyses, we considered the environment parameter's change between the current time and a time 5, 10, or 15 minutes earlier.

The effects of an environment parameter's change on TA and PAQA are presented in Figures 5 and 6. Figure 5 illustrates the thermal acceptability against the temperature increase during 15 minutes for the AC sleeping group while in an indoor environment with air-conditioning off. Any acceptability responses not associated with a continuous past 15-minute monitoring data were excluded from the analysis. With binning at ±0.5 °C, the proportions of subject responses indicating thermally acceptable conditions in response to temperature changes over 15 minutes of 0, +1, +2 and +3 °C were 65%, 50%, 33% and 0%, respectively. These data indicate that, in Singapore, a short-term transition to a warmer condition tends to decrease thermal satisfaction. The explanation is supported by evidence from previous discussion, where an unacceptable thermal choice is more likely to occur for the AC sleeping group when these subjects, who live in a climate that is consistently warm and humid, are in uncontrollable environments and experience an increase of temperature.
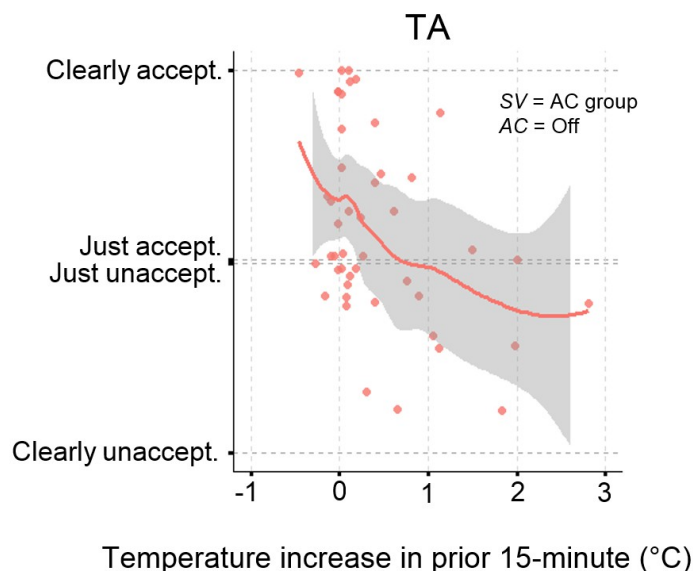

Figure 5. Thermal acceptability trends to prior 15-minute temperature difference for AC sleeping ventilation (*SV*) group at *AC* turned off condition. Regression line and shading are defined in Fig 3.

Figure 6 presents the PAQA responses for two participants (NV-M-01 and NV-M-02) plotted against the CO_2 mixing ratio increase experienced across a 15-minute time step. The motivation is to explore individual reactions to a CO_2 mixing ratio change, considering subjects of the same sex and sleeping ventilation habit. The filled color of the scatterplot shows the most recent measured CO_2 mixing ratio (i.e., at the PAQA response time). By inspection, subject NV-M-01 was sensitive to and dissatisfied with a high CO_2 mixing ratio environment. In contrast, subject NV-M-02 was more tolerant, reporting a high PAQA across a wide range of CO_2 mixing ratio regardless of concentration variation.
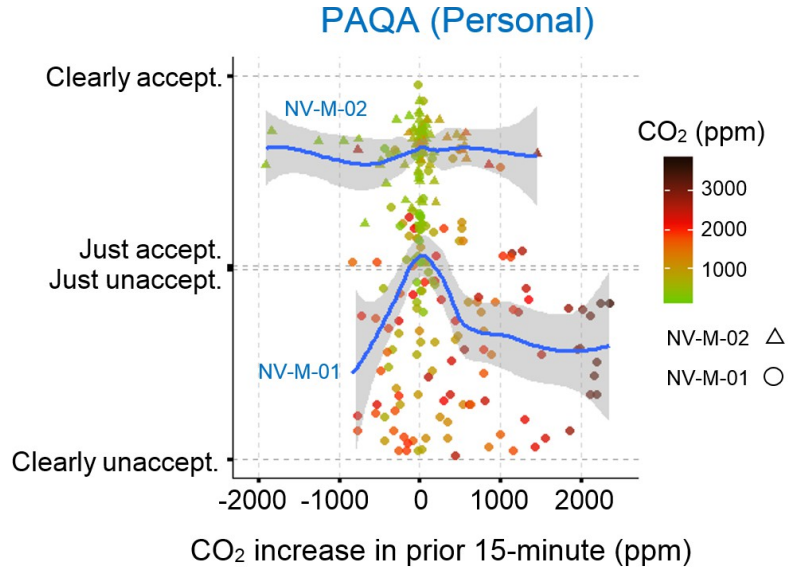
Figure 6. Personal perceived air quality acceptability (for subjects NV-M-01 and NV-M-02) in relation to change in CO_2 mixing ratio experienced during a 15-minute period. Regression line and shading are defined in Fig 3.

4   Simulation models

Thermal and perceived air quality acceptability simulations were performed by multiple linear regression (MLR) and Gaussian process (GP). Sensitivity tests, using GP, on different combinations of variables are summarized in Table 2. Additional tests, using both MLR and GP, with more parameter combinations are presented in the supporting information, Table S2. The tested variables included the measured physical parameters (T_a, RH and CO_2), the clustering factors (sleeping ventilation (SV), air-conditioning status (AC) and location (Loc)) and the former 5 (ΔT_{a_5}, $\Delta RH_{\_5}$, ΔCO_{2_5}), 10 and 15 min physical parameter differences. Also, the environmental changes of air-conditioning status and location in past 5 ($AC_{\_5}$, $Loc_{\_5}$), 10 and 15 min are considered. The subject identification, "ID", was used.

From Table S2, it is clear that the Gaussian process (GP) has a systematic superior predicting performance than multiple linear regression (MLR). This outcome may be due to the GP ability to model non-linear (and non-monotonic) relationships between acceptabilities and the explanatory variables (e.g., Figures 3 and 4). In Table 2, tests 1 – 3 (T1-T3) suggested that the single predictor of temperature, humidity and CO_2 mixing ratio did not show good acceptability predictions. Despite an improvement found in T4 by using all three parameters, the simulation performance was still not promising for TA (r^2, MSE, MAE; 0.17, 0.18, 0.35) and PAQA (0.26, 0.19, 0.35). Adding the environmental parameter changes in the previous 5, 10 and 15 minutes in T8 did not improve simulation results as compared with T4. This outcome suggests that acceptability responses from this subject group may not only be initiated by physical parameter changes, which is also evidenced in the "NV-M-02" data in Figure 6. In tests T9 – T13, significant model improvement was found by introducing the clustering factors, especially for location and sleeping ventilation mode, where the best simulation was made by including SV, AC and Loc in T13, which improved r^2 to 0.27 from 0.17 for T4. Knowing the location, a subject's sleeping ventilation habit, and the air-conditioning operation status improved prediction abilities; however, these may not be easily determined if used in practical application (i.e., outside of a research project). Incorporating the additional information would require extra effort and would rely on a participant's self-

report. The needed information is not likely to be automatically identified by any existing sensor. Even if it is possible that such parameters could be autonomously determined by future technologies, the efficiency and accuracy in collecting such information could vary across individuals and could introduce additional sources of error in acceptability simulations.

Subject identification was introduced in tests T14 – T17 to explore the effectiveness of accounting for personal differences in the acceptabilities simulations. Significant predictability improvement was realized by adding subject identity. This outcome is not surprising, given how much variability is associated with individual people. However, adding extra predictor variables for simulations in test T18 did not necessarily show higher predictive power.

The tests T19 – T24 attempted to reduce the number of separate predictors relative to test T17, with the goal of removing the most challenging to obtain variables: (a) the CO_2 sensor (because it is expensive and energy intensive); and (b) AC and Loc (self-recording air-conditioning status in every location change is tedious). When all the variables were removed (T19) a small performance reduction was found in thermal acceptability (r^2 reduced from 0.34 to 0.31), while a substantial reduction was observed in simulating PAQA (r^2 reduced from 0.40 to 0.31). These results indicate that removing CO_2, AC and Loc did not have a large effect on the predictability of thermal acceptability. Higher PAQA prediction performance was observed when AC and Loc were reintroduced in T24 (r^2 =0.38), but it is still weaker than T17. These results suggest the possibility of a less expensive but efficient alternative: longitudinally recording only T_a and RH for predicting a subject's thermal acceptability. However, the CO_2 mixing ratio remains a prime factor to be measured for accurate simulation of perceived air quality if the location and current air-conditioning status are not known.

T17 is chosen to be the representative model for further discussion because it has the highest predictive power among all tests in Table 2. Figure 7a presents the TA and PAQA validation data from GP models (T17). To test the effectiveness of this general model on the ability to predict acceptability for a specific individual, Figure 7b graphs the validation performances of the model in estimating acceptability of TA and PAQA from two representative individual subjects (AC-M-01 and NV-M-01). For "AC-M-01", poorer TA (r^2=0.18) and PAQA (r^2=0.14) was predicted. A lower TA (r^2=0.26) but higher PAQA (r^2=0.43) for "NV-M-01" was observed in comparison with the general model T17 in Table 2. Overall, the performance of the general model for predicting a specific subject's acceptability responses are reduced relative to the performance in predicting collective responses across all subjects.

Instead of a "general" cohort, an individual simulation approach (trained and validated only using the individual samples) is proposed to test the possibility of predictive power improvement. An individual model is personally dependent and therefore the subject's sleeping ventilation habit and ID become trivial as predictor variables. The individual model approach was again tested using AC-M-01 and NV-M-01 sample data (70% for training and 30% for validation). Combinations of predictor variables were tested and chosen using the best simulation performance for each individual model, as presented in Figure 7c. For TA simulation, predictor variables used for AC-M-01 were T_a, RH, CO_2, ΔT_{a_10} and $\Delta RH_{\_10}$; for NV-M-01, these to variables were added Loc and ΔCO_{2_10}. In the PAQA simulation, parameters used for both subjects were CO_2 and ΔCO_{2_15}; in addition, T_a and ΔT_{a_15} were included for NV-M-01. This individual simulation approach produced insignificant improvement at the individual level (Figure 7b vs. 7c) in each case except "TA – AC-M-01".

However, the physical parameter differences (ΔT_{a_t}, $\Delta RH_{\_t}$ and ΔCO_{2_t}) became more important than the clustering factors (*AC* and *Loc*).

Since the general and individual simulation approaches may provide similar performance, but with different predictor variables, the criteria for selecting a simulation method would depend on the motivation of prediction. The general approach requires more clustering factors (*SV*, *AC* and *Loc*), which may entail extra cost and error to develop the model, while its major advantage is its freedom from additional acceptability surveys for prediction with new subjects. In contrast, for the individualized approach, the predictor variables are easier to collect, but each new subject has to participate in an acceptability experiment before any prediction can be made available. These findings motivate future work that seeks to further develop an individual acceptability simulation approach using a series of longitudinal environment data monitored from wearable sensors. The potential applications could be associated with, for example, smart air-conditioning systems that communicate with portable personal sensors to achieve personal comfort environment in private places, such as vehicles, offices or bedrooms.

Table 2. Parameter sensitivity tests on the simulation of thermal and perceived air quality acceptabilities using Gaussian process (GP) models.

| Parameters	T1	T2	T3	T4	T8	T9	T10	T12	T13	T14	T17*	T18	T19	T21	T24
T_a	X			X	X	X	X	X	X	X	X	X	X	X	X
RH		X		X	X	X	X	X	X	X	X	X	X	X	X
CO_2			X	X	X	X	X	X	X	X	X	X			
SV									X		X	X		X	X
AC							X		X		X	X			X
Loc						X			X		X	X			X
ΔT_{a_5}					X							X			
$\Delta RH_{\_5}$					X							X			
ΔCO_{2_5}					X							X			
$AC_{\_5}$							X					X			
$Loc_{\_5}$						X						X			
ΔT_{a_10}					X							X			
$\Delta RH_{\_10}$					X							X			
ΔCO_{2_10}					X							X			
$AC_{\_10}$							X					X			
$Loc_{\_10}$						X						X			
ΔT_{a_15}					X							X			
$\Delta RH_{\_15}$					X							X			
ΔCO_{2_15}					X							X			
$AC_{\_15}$							X					X			
$Loc_{\_15}$						X						X			
ID										X	X	X	X	X	X
TA GP – r^2	0.01	0.02	0.07	0.17	0.15	0.21	0.17	0.25	0.27	0.31	0.34	0.29	0.31	0.32	0.33
GP – MSE	0.22	0.22	0.20	0.18	0.18	0.17	0.18	0.16	0.16	0.15	0.14	0.16	0.15	0.15	0.15
GP – MAE	0.39	0.38	0.37	0.35	0.35	0.33	0.35	0.32	0.31	0.30	0.30	0.31	0.30	0.30	0.30
PAQA GP – r^2	0.03	0.06	0.06	0.26	0.25	0.35	0.26	0.30	0.35	0.36	0.40	0.36	0.28	0.31	0.38
GP – MSE	0.26	0.25	0.22	0.19	0.20	0.17	0.20	0.18	0.17	0.17	0.15	0.17	0.19	0.18	0.16
GP – MAE	0.42	0.41	0.37	0.35	0.36	0.34	0.35	0.34	0.33	0.33	0.31	0.34	0.34	0.34	0.32

* Represents the best simulation model
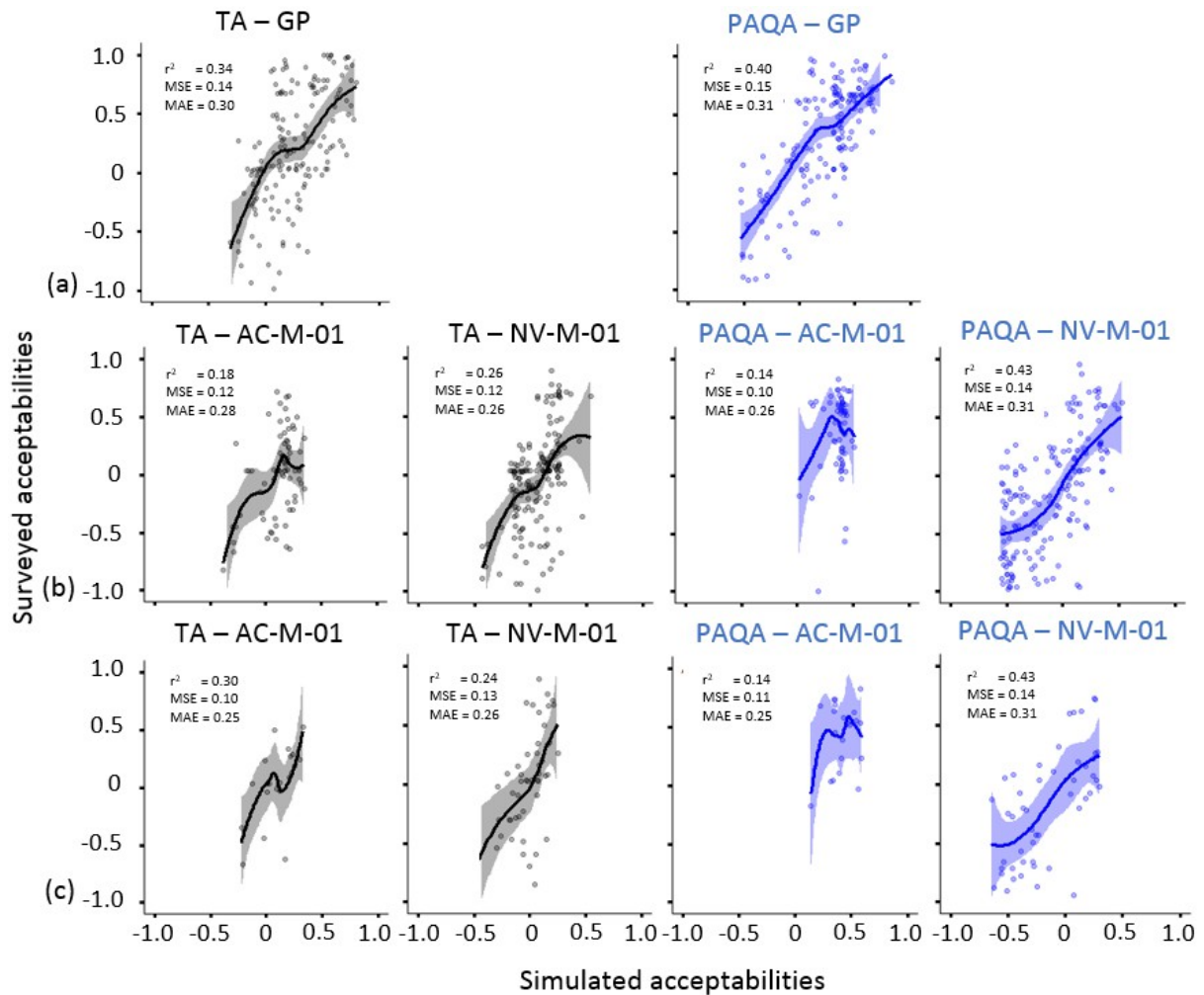
Figure 7. Validation performance of acceptabilities simulation models: (a) General model validation for acceptabilities (TA and PAQA) via GP model (Test 17); (b) Personal (AC-M-01 and NV-M-01) acceptabilities sample validation by general GP-trained model (Test 17); and (c) Personal acceptabilities sample validation by individual model with the best predictors combination. Regression line and shading are defined in Fig 3.

6   Conclusions

Longitudinal monitoring experiments were conducted to investigate individual thermal acceptability (TA) and perceived air quality acceptability (PAQA) with respect to objective physical parameters (temperature, relative humidity, and CO_2 concentration), individual location, air-conditioning status, occupants' sleeping ventilation habits and personal environmental exposure history. A thermal and perceived air quality acceptability model with good predictive power was developed.

The 15 participants from Singapore's modern tropical environment spent an average of 96% of their time indoors, primarily in the home (61%) and the workplace (26%). High average satisfaction proportions were recorded for TA and PAQA at home (82%, 84%) and in the workplace (83%, 91%); corresponding results were relatively low

in transport environments (55%, 36%). Air temperature and relative humidity in non-air-conditioned homes were found to be similar to the outdoor environment; in air-conditioned homes, corresponding average values were 2.6 °C cooler with 9% lower relative humidity than non-air-conditioned homes.

A tenuous relationship was found between 9acceptability scores (both TA and PAQA) and the measured environmental parameters (temperature, humidity, CO_2 level); however, knowing the location of subjects (e.g., home vs. workplace) made the associations clearer. Furthermore, the group of subjects who slept with air-conditioning was found to generally report lower acceptability values in environments other than the home as compared with the group that slept without air conditioning. The overcooled workplace reported in some prior studies was not commonly observed in the data collected here; nevertheless, this is not a representative population sample. Thermal dissatisfaction was observed for the group who slept with air-conditioning if the workplace temperature was lower than 25 °C. In addition, a short-term transition to a warmer condition tended to decrease thermal satisfaction for air-conditioning sleeping group in non-air-conditioned places. However, evidence also indicated that the acceptabilities trend might be highly variable across subjects, even among those with similar sleeping ventilation conditions.

Gaussian process modelling was found to be more effective than a multiple linear regression approach for acceptability simulations. A general modelling approach could yield predictions for new subjects without the need for an extra acceptability survey, but more complex predictor variables (location and corresponding air-conditioning status) were required. Conversely, for the individual modelling approach (trained and validated by personal data), data for each subject must be generated by way of participation in an acceptability experiment but the required variables (time series temperature, humidity and CO_2 level) for model construction are easier to obtain. The predictive powers of the general and individualized approaches were comparable, and the selection criteria may depend on the specific motivation for making predictions.

This study showed the richness of analysis and insights that can be obtained with longitudinal experiments following people across multiday periods. The acceptability simulation models developed here open a topic for expanded future studies to better understand the factors that influence personal comfort.

Acknowledgements

References

[1] D. Clements-Croome, Ed., *Creating the Productive Workplace*, 2nd ed. New York: Taylor & Francis (2006).

[2] M. Frontczak, P. Wargocki, Literature survey on how different factors influence human comfort in indoor environments, Build. Environ. 46 (2011) 922–937.

[3] O.A. Seppänen, W. Fisk, Some quantitative relations between indoor environmental quality and work performance or health, HVAC&R Research 12 (2006) 957–973.

[4] S. Tanabe, N. Nishihara, M. Haneda, Indoor temperature, productivity and fatigue in office tasks, HVAC&R Research 13 (2007) 623–633.

[5] P. Wargocki, O.A. Seppänen, Eds., Indoor Climate and Productivity in Offices, Guidebook No. 6. Brussels, Belgium: Federation of European Heating and Air-conditioning Associations (2006).

[6] O.A. Seppänen, W.J. Fisk, Association of ventilation system type with SBS symptoms in office workers, Indoor Air 12 (2002) 98–112.

[7] P. Wargocki, D.P. Wyon, J. Sundell, G. Clausen, P.O. Fanger, The effects of outdoor air supply rate in an office on perceived air quality, sick building syndrome (SBS) symptoms and productivity, Indoor Air 10 (2000) 222–236.

[8] P. Wargocki, D.P. Wyon, Y.K. Baik, P.O. Fanger, Perceived air quality, sick building syndrome (SBS) symptoms and productivity in an office with two different pollution loads, Indoor Air 9 (1999) 165–179.

[9] D.P. Wyon, The effects of indoor air quality on performance and productivity, Indoor Air 14 Suppl. 7 (2004) 92–101.

[10] P.O. Fanger, Thermal Comfort: Analysis and Applications in Environmental Engineering, Copenhagen: Danish Technical Press (1970).

[11] A.P. Gagge, J.A.J. Stolwijk, J.D. Hardy, Comfort and thermal sensations and associated physiological responses at various ambient temperatures, Environ. Res. 1 (1967) 1–20.

[12] P.M. Bluyssen, S. Janssen, L.H. van den Brink, and Y. de Kluizenaar, Assessment of wellbeing in an indoor office environment, Build. Environ. 46 (2011) 2632–2640.

[13] R.J. de Dear, G.S. Brager, Developing an adaptive model of thermal comfort and preference, ASHRAE Trans. 104 Pt. 1 (1998) 145–167.

[14] J.F. Nicol, M.A. Humphreys, Adaptive thermal comfort and sustainable thermal standards for buildings, Energy Build. 34 (2002) 563–572.

[15] A.C.K. Lai, K.W. Mui, L.T. Wong, L.Y. Law, An evaluation model for indoor environmental quality (IEQ) acceptance in residential buildings, Energy Build. 41 (2009) 930–936.

[16] Z. Lin, S. Deng, A questionnaire survey on sleeping thermal environment and bedroom air conditioning in high-rise residences in Hong Kong, Energy Build. 38 (2006) 1302–1307.

[17] M.J. Mendell, G.A. Heath, Do indoor pollutants and thermal conditions in schools influence student performance? A critical review of the literature, Indoor Air 15 (2005) 27–52.

[18] D. Norbäck, K. Nordström, Sick building syndrome in relation to air exchange rate, CO_2, room temperature and relative air humidity in university computer classrooms: An experimental study, Int. Arch. Occup. Environ. Health 82 (2008) 21–30.

[19] P. Wargocki, D.P. Wyon, The effects of moderately raised classroom temperatures and classroom ventilation rate on the performance of schoolwork by children (RP-1257), HVAC&R Research 13 (2007) 193–220.

[20] J. Langevin, P.L. Gurian, J. Wen, Tracking the human-building interaction: A longitudinal field study of occupant behavior in air-conditioned offices, J. Environ. Psychol. 42 (2015) 94–115.

[21] Z. Pei, B. Lin, Y. Liu, Y. Zhu, Comparative study on the indoor environment quality of green office buildings in China with a long-term field measurement and investigation, Build. Environ. 84 (2015) 80–88.

[22] C. Chun, A. Kwok, T. Mitamura, N. Miwa, A. Tamura, Thermal diary: Connecting temperature history to indoor comfort, Build. Environ. 43 (2008) 877–885.

[23] M.O. Fadeyi, Initial study on the impact of thermal history on building occupants' thermal as sessments in actual air-conditioned office buildings, Build. Environ. 80 (2014) 36–47.

[24] S. Schiavon, S. Altomonte, Influence of factors unrelated to environmental quality on occupant satisfaction in LEED and non-LEED certified buildings, Build. Environ. 77 (2014) 148–159.

[25] R. De Vecchi, C. Cândido, R. Lamberts, Thermal history and its influence on occupants' thermal acceptability and cooling preferences in warm-humid climates: A new desire for comfort? in Proceedings of the 7th Windsor Conference: The Changing Context of Comfort in an Unpredictable World, London (2012), http://nceub.org.uk.

[26] H. Kim, C. Chun, A. Kwok, A. Ota, A. Tamura, Cross-city comparison of indoor air temperatures in air-conditioned spaces, Indoor Air 21 (2011) 311–318.

[27] L. Fang, G. Glausen, P.O. Fanger, Impact of temperature and humidity on perception of indoor air quality during immediate and longer whole-body exposures, Indoor Air 8 (1998) 276–284.

[28] X. Chen, Q. Wang, J. Srebric, M.O. Fadeyi, Data-driven state-space modeling of indoor thermal sensation using occupant feedback, American Control Conference (ACC), Portland, Oregon, USA (2014), 1710–1715.

[29] E. Foda, I. Almesri, H.B. Awbi, K. Sirén, Models of human thermoregulation and the prediction of local and overall thermal sensations, Build. Environ. 46 (2011) 2023–2032.

[30] H. Zhang, E.A. Arens, W. Pasut, Air temperature thresholds for indoor comfort and perceived air quality, Build. Res. Inf. 39 (2011) 134–144.

[31] Y. Zhao, H. Zhang, E.A. Arens, Q. Zhao, Thermal sensation and comfort models for non-uniform and transient environments, part IV: Adaptive neutral setpoints and smoothed whole-body sensation model, Build. Environ. 72 (2014) 300–308.

[32] E.T. Gall, T. Cheung, I. Luhung, S. Schiavon, W.W. Nazaroff, Real-time monitoring of personal exposures to carbon dioxide, Build. Environ. 104 (2016) 59–67.

[33] CO2Meter, Datasheet: CO2, Temperature and %RH Data Logger (2014) http://www.co2meters.com/Documentation/Datasheets/DS-CM0016-17-18-19.pdf.

[34] R Development Core Team, R: A language and environment for statistical computing, Available: http://www.gbif.org/resource/81287. [Accessed: 06-Jul-2016].

[35] C.E. Rasmussen, C.K.I. Williams, Gaussian Processes for Machine Learning, Cambridge: The MIT Press (2006).

[36] G. Seni, J.F. Elder, Ensemble Methods in Data Mining: Improving Accuracy Through Combining Predictions, Morgan & Claypool (2010).

[37] P. Zhang, Model selection via multifold cross validation, Ann. Stat. 21 (1993) 299–313.

[38] T. Moreno, C. Reche, I. Rivas, M.C. Minguillón, V. Martins, C. Vargas, G. Buonanno, J. Parga, M. Pandolfi, M. Brines, M. Ealo, A.S. Fonseca, F. Amato, G. Sosa, M. Capdevila, E. de Miguel, X. Querol, W. Gibbons, Urban air quality comparison for bus, tram, subway and pedestrian commutes in Barcelona, Environ. Res. 142 (2015) 495–510.

[39] S.C. Sekhar, Space temperature difference, cooling coil and fan—energy and indoor air quality issues revisited, Energy Build. 37 (2005) 49–54.

[40] D. Rim, S. Schiavon, W.W. Nazaroff, Energy and cost associated with ventilating office buildings in a tropical climate, PLoS One 10 (2015) e0122310.

[41] S.C. Sekhar, Higher space temperatures and better thermal comfort — a tropical analysis, Energy Build. 23 (1995) 63–70.

[42] A. Chen, V.W.C. Chang, Human health and thermal comfort of office workers in Singapore, Build. Environ. 58 (2012) 172–178.

[43] N. Kishnani, B.K. Tan, R. Bozovic Stamenovic, D. Prasad, F. Faizal, Post-occupancy evaluation of Green Mark-rated buildings in Singapore, World Sustainable Building Conference, Barcelona (2014) 455–461.

[44] C.M. Cândido, R. de Dear, R. Lamberts, L. Bittencourt, Cooling exposure in hot humid climates: Are occupants 'addicted'? Archit. Sci. Rev. 53 (2010) 59–64.