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Bayesian thermal comfort model

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Nomenclature

A, *B*	Events
AC	Air-conditioned
APD	Actual Percentage Dissatisfied
abs	of absolute
C_0	y – intercept of Predicted Mean Vote (*PMV*) – Thermal Sensation Vote (*TSV*) plot
C_1	Slope of *PMV*–*TSV* plot
C_L	Clothing value (clo)
F	Distribution function
k	Dissatisfaction cases reported for each vote
n	Number of cases surveyed for each vote
n_2	Target sample size
M_e	Occupant metabolic rate (Met)
NV	Naturally ventilated
P	Probability function
PMV	Predicted mean vote
p	p-value of a statistical test
R_h	Relative humidity (%)
SD	Standard deviation
T_a	Air temperature (^oC)
T_r	Mean radiant temperature (^oC)
TSV	Thermal sensation vote
v_a	Air velocity (ms^{-1})
x	Dummy variable
φ	Predicted percentage dissatisfied (*PPD*)
σ	Shape factor
ε	Error
Σn	Total sample size
Σk	Total dissatisfied sample

Superscript

–	of mean value
’	of posterior estimate

Subscript

1, 2	of conditions 1, 2
i	of the ith item
max	of maximum
rms	of root-mean-square

Abstract

Thermal comfort assessment is a prime measure in indoor environment design to evaluate occupant satisfaction. Fanger's thermal comfort model using heat balance theory conducted by chamber test has been widely adopted for thermal environment design criteria. However, rising numbers of thermal comfort field studies show that Fanger's model is not a good predictor of actual thermal sensation and many field measurements were statistically insignificant. This study proposes a Bayesian approach to update our current beliefs about thermal comfort and shows that the maximum likelihood of posterior estimates is close to the actual percentage dissatisfied (*APD*) obtained from large sample field surveys. For small sample sizes, the Bayesian estimation is close to Fanger's prediction and gives a solution for the discrepancy of Fanger's model. Congruence between Fanger's model prediction and contemporary field survey data is quantified. This quantitative assessment on the belief in newly yielded thermal comfort data can be a solution to the choice of thermal comfort criteria in future thermal environment designs.

1. Introduction

Thermal comfort, a key indoor environmental quality concern for homes, offices and classrooms, is closely related to energy use, occupant productivity and student learning performance [1–3]. Thermal comfort models for predicting occupant satisfaction and for designing an acceptable thermal environment can be found in literature; the 225-node finite element model [4], predicted mean vote (*PMV*) model [5], 25-node basic heat flow model [6], 2-node basic heat flow model [7] and 2-node with transient response model [8] are a few examples.

Developed by Fanger using chamber test results under steady state conditions, the *PMV* model uses six key parameters, namely, air temperature (T_a), mean radiant temperature (T_r), air velocity

(v_a), relative humidity (R_h), occupant metabolic rate (M_e) and clothing value (C_L), to get the predicted percentage dissatisfied (*PPD*) under given thermal conditions. Despite the fact that it is widely used for designing indoor thermal environments [9], a number of discrepancies between actual percentage dissatisfied (*APD*) related to thermal sensation vote (*TSV*) and predicted percentage dissatisfied (*PPD*) determined from predicted mean vote (*PMV*) have been revealed [10, 11]. These discrepancies can be grouped into two major categories: (i) *PMV* against *TSV* as presented in Table 1; and (ii) *PPD* against *APD* as presented in Table 2. Moreover, the usefulness of extrapolated *PMV-TSV* regressions has received criticism as extreme thermal conditions are rare in many field studies (Table 1).

Using the values of intercept (C_0) and slope (C_1) reported in the literature (Table 1), linear regressions for category (i) are described by the following equation:

$$TSV = C_1 \times PMV + C_0 \qquad \ldots(1)$$

Two phenomena were observed in this category. First, a steep slope ($C_1>1$) was generally found in air-conditioned (*AC*) buildings and a flat slope ($C_1<1$) in naturally ventilated (*NV*) buildings during summer. In other words, occupants in *AC* buildings, especially in offices and classrooms where they have limited control over the thermal environmental settings, were more sensitive to the perception of thermal comfort than occupants in *NV* buildings and had higher expectations in a narrow thermal comfort range [28, 29]. Fanger and Tofum confirmed this phenomenon and extended the *PMV* model to minimize the discrepancies [30]. Although occupants in the studies by Fato et al. and Han et al. might have higher expectations for heating during winter in *NV* buildings [16, 22], rural residents (i.e. with lower socioeconomic status) in different climate zones were reported to have high levels of tolerance to climatic conditions [28]. Second, occupants in

NV buildings were found to be adapting to a cooler environment ($+C_0$) in winter and a warmer environment ($-C_0$) in summer for thermal neutrality (TSV = 0). This can be explained by the adaptive approach to outdoor environment [31]. Occupants in *AC* or mixed-mode buildings, however, were found having thermal comfort responses influenced by the past thermal history in the buildings and differences in levels of perceived control [29].

Occupants' satisfaction to the thermal environment by field survey was also reported differently from Fanger's model. Using the ASHRAE database, Humphreys and Nicol reported the differences between Fanger's predicted percentage of dissatisfied (φ) and actual percentage of dissatisfaction (*APD*) in a number of small sampled surveys. Some examples of category (ii) are summarized in Table 2. A study conducted in two inter-tropical sub-Saharan African cities showed that occupants preferred a cooler environment in the hotter climate zone during the Harmattan season [10]. In Taiwan, Cheng et al. found dissatisfaction rates higher in *NV* campus dormitories than in *AC* ones during the summer period [25] and a chamber test by Hwang et al. suggested people in hot-humid climates would prefer a slightly cooler environment (TSV = –0.4) [26]. In Harbin, a winter field study indicated that the thermal neutrality of occupants in a slightly cool environment was biased on the warm side (a minimum *APD* of 7.5% at TSV = 0.5) [27]. For resolving the discrepancies in this category, Humphreys and Nicol discussed the need for caution when using a large scale model in small sample tests [11] while Becker and Paciuk introduced the non-symmetrical dissatisfaction rates for hot and cold sensations [24].

Although the adequacy of Fanger's model for evaluating thermal comfort is questioned, another model as an accurate predictor of actual thermal sensation is yet to be proposed. As thermal comfort in a thermal environment is never conclusive, similar discrepancies and questions will undoubtedly keep taking place in future sustainable environmental designs. One may ask, “Which reference, Fanger’s model or field survey outcome, shall be the design criterion for built thermal environment?” This is a fundamental problem of judgmental decision making based on the best information available and an epistemic approach is required for estimating the acceptance of a thermal environment [32].

To update our current beliefs about thermal comfort, this study presents a Bayesian approach and demonstrates the usefulness of the approach through contemporary field survey data and Fanger’s *PMV-PPD* model. The findings provide a solution to the choice of thermal comfort criteria in future thermal environment designs.

Table 1. Occupants' thermal sensation votes (*TSV*) in various studies

Ref.	Location	Building	Type of Ventilation	Season	Total Sample Size, Σ*n*	C_1	C_0	*TSV*						
								-3	-2	-1	0	1	2	3
[12]	Italy	Classroom	Mixed	Mixed	959	0.76	-0.51	-	-	-	-	-	-	-
[13]	Taiwan	Classroom	Mixed	Winter	1294	0.50	0.13	18	95	282	623	188	44	44
[14]	China	Residential	Mixed	Summer	110	1.69	-2.60	1	3	4	54	30	13	5
[15]	Australia	Office	*AC*	Mixed	1234	3.10	-0.49	-	-	-	-	-	-	-
[2]	Hong Kong	Office	*AC*	Mixed	1273	3.08	2.97	48	100	307	606	174	28	10
[2]	Hong Kong	Classroom	*AC*	Winter/Spring	312	5.76	2.54	5	19	92	146	36	10	4
[16]	Bari (Italy)	-	*AC*	Winter	133	1.93	0.51	0	1	5	47	56	22	2
[16]	Bari (Italy)	-	*AC*	Summer	250	2.04	-0.97	0	0	9	96	98	41	6
[17]	Brazil	-	*NV*	Mixed	1150	0.56	-0.01	-	-	-	-	-	-	-
[16]	Bari (Italy)	-	*NV*	Summer	423	0.99	-0.30	0	0	16	119	128	118	42
[18]	Ilam (Iran)	Residential	*NV*	Summer	513	0.69	-0.74	-	-	-	-	-	-	-
[19]	India	Residential	*NV*	Summer	294	0.70	-1.04	0	0	11	107	100	50	26
[20]	Singapore	Residential	*NV*	Mixed	538	0.81	-0.48	-	-	-	-	-	-	-
[21]	Indonesia	Residential	*NV*	Mixed	525	1.33	-1.61	28	83	78	82	97	26	131
[16]	Bari (Italy)	-	*NV*	Winter	1034	1.61	0.70	37	93	324	367	162	43	8
[22]	Hunan (China)	Residential (Urban)	*NV*	Winter	53	1.24	0.06	1	9	12	30	1	0	0
[22]	Hunan (China)	Residential (Rural)	*NV*	Winter	50	0.48	-0.54	3	5	16	24	1	1	0
[23]	Hunan (China)	Classroom	*NV*	Spring	1273	0.39	0.15	5	8	122	993	120	21	4

'-' indicates the *TSV* values are not available in the corresponding studies

Table 2. Review of actual percentage dissatisfied (*APD;* %) in various studies

Ref.	Location	Ventilation	Season	Total Sample Size, Σ*n*	*TSV*						
					-3	-2	-1	0	1	2	3
[24]	Israel	Heating	Winter	189	100	64	50	9	19	14	14
[24]	Israel	NV	Summer	205	-	33	36	18	86	83	100
[25]	Taiwan	AC	Summer	600	-	5	5	6	10	18	57
[25]	Taiwan	NV	Summer	619	28	32	6	7	21	54	65
[10]	Ngaoundere	NV	Harmattan	119	100	20	22	13	25	50	100
[10]	Kousseri	NV	Harmattan	95	100	84	20	20	18	-	100
[26]	Taiwan	AC	N/A	27	90	49	22	20	41	80	95
[27]	Harbin	NV	Winter	120	100	100	43	12	27	25	50
					PMV						
					-3	-2	-1	0	1	2	3
Predicted percentage dissatisfied (*PPD*) in Fanger's model [5]					99	75	25	05	25	75	99

2. Methodology

A Bayes' theorem can be applied in such a way that even for a sample size not large enough for making a managerial decision to supersede existing understandings of thermal sensation, the importance of relevant survey data is not ignored. The general formulation of Bayes' theorem for various applications is available in open literature [33] while the specific elements for the formulation of prior and posterior probabilities are described below.

In this study, the Bayesian approach is used to predict the occupant thermal responses to an environment using the already available model predictions (event *A*) and the responses surveyed (event *B*). Bayes' theorem relates the conditional and marginal probabilities of events *A* and *B*, where *B* has a non-vanishing probability. Its key idea is that the probability of an event *A* given an event *B* depends not only on the relationship between events *A* and *B* but also on the marginal probability of occurrence of each event.

For example, if the dissatisfaction rate of a thermal environment determined by a sample survey is known to be 90% accurate, it could be due to the 10% incorrectly identified survey cases (false positives), 10% missed cases (false negatives), or a mix of both. Application of Bayes' theorem, given an observed dissatisfaction rate, allows the calculation of conditional probabilities for any of the above cases.

Hence, for A_i, a set of mutually exclusive and exhaustive events A describing the existing understanding of dissatisfaction rates (for i=1,2,…) of a specific thermal environment, given event B, a new dissatisfaction observed in that environment (denoted as $B=k/n$), the posterior probability $P(A_i|B)$ is defined as,

$$P(A_i \mid B) = \frac{P(A_i)P(B \mid A_i)}{\sum P(A_i)P(B \mid A_i)} \qquad \text{… (2)}$$

$P(B \mid A_i)$ can be worked out by the likelihood function as follows, where n and k are the number of cases surveyed and the dissatisfaction cases reported respectively for each vote,

$$P(B \mid A_i) = \binom{n}{k} P(A_i)^k \left(1 - P(A_i)\right)^{n-k} \qquad \text{… (3)}$$

The prior estimate is a distribution function F of Fanger's predicted percentage of dissatisfied occupants φ,

$$P(A_i) = F(\overline{\varphi}, \sigma) \qquad \text{… (4)}$$

where $\overline{\varphi}$ is a function of PMV as expressed below [5], given the clothing value C_L (clo), occupant metabolic rate M_e (Met), relative humidity R_h (%), mean radiant temperature T_r (ºC), air temperature T_a (ºC) and air velocity v_a (ms^{-1}),

$$\overline{\varphi} = 1 - 0.95\exp\left(-0.03353PMV^4 - 0.2179PMV^2\right);\ -3 \le PMV \le 3 \qquad \text{… (5)}$$

$$PMV = PMV\left(T_a, T_r, R_h, v_a, M_e, C_L\right) \quad \text{… (6)}$$

2.1 Prior estimates and prior distribution functions

Normal distribution (or its transformation such as lognormal distribution) is an appealing and good model for explaining many forms of natural continuous variation and is generally adopted in many biological sciences and engineering applications. The prior predicted percentage of dissatisfied occupants is assumed to be a normal (or lognormal) distribution; two simple distribution functions, namely normal distribution function $F_1=F(\sigma_1)$ and lognormal normal prior distribution function $F_2=F(\sigma_2)$, with $\bar{x}$ and σ as the mean and standard deviation of variable x respectively, are considered as priors,

$$F = \int \frac{e^{-(x-\bar{x})^2/2\sigma^2}}{\sigma\sqrt{2\pi}} dx \;\; ; \;\; x = \begin{cases} \varphi \\ ln\,\varphi \end{cases} ; \;\; \sigma = \begin{cases} \sigma_1/10 \\ ln\,\sigma_2 \end{cases} ; \;\; 0 \le x \le 1 ; \;\; F = 1 \quad \text{… (7)}$$

Figure 1 illustrates some examples of prior estimates for the predicted percentage of dissatisfied occupants in a thermal environment when: (i) $PMV=0$; and (ii) $PMV=\pm 1.5$.

In Figure 2 are examples of distributions for the predicted percentage of dissatisfied occupants in 8 university teaching rooms from a previous study [2]. As shown in the figure, the average *TSV* is from −1.1 to 0.4 with a standard deviation (*SD*) from 0.7 to 1.1, indicating that the distribution of predicted percentage of dissatisfied occupants can be reasonably approximated using F_1 (except cases (f) & (g)) and F_2 (except case (a)) ($p \geq 0.1$, Chi-square). The two prior functions are thus adopted in the model development described below.

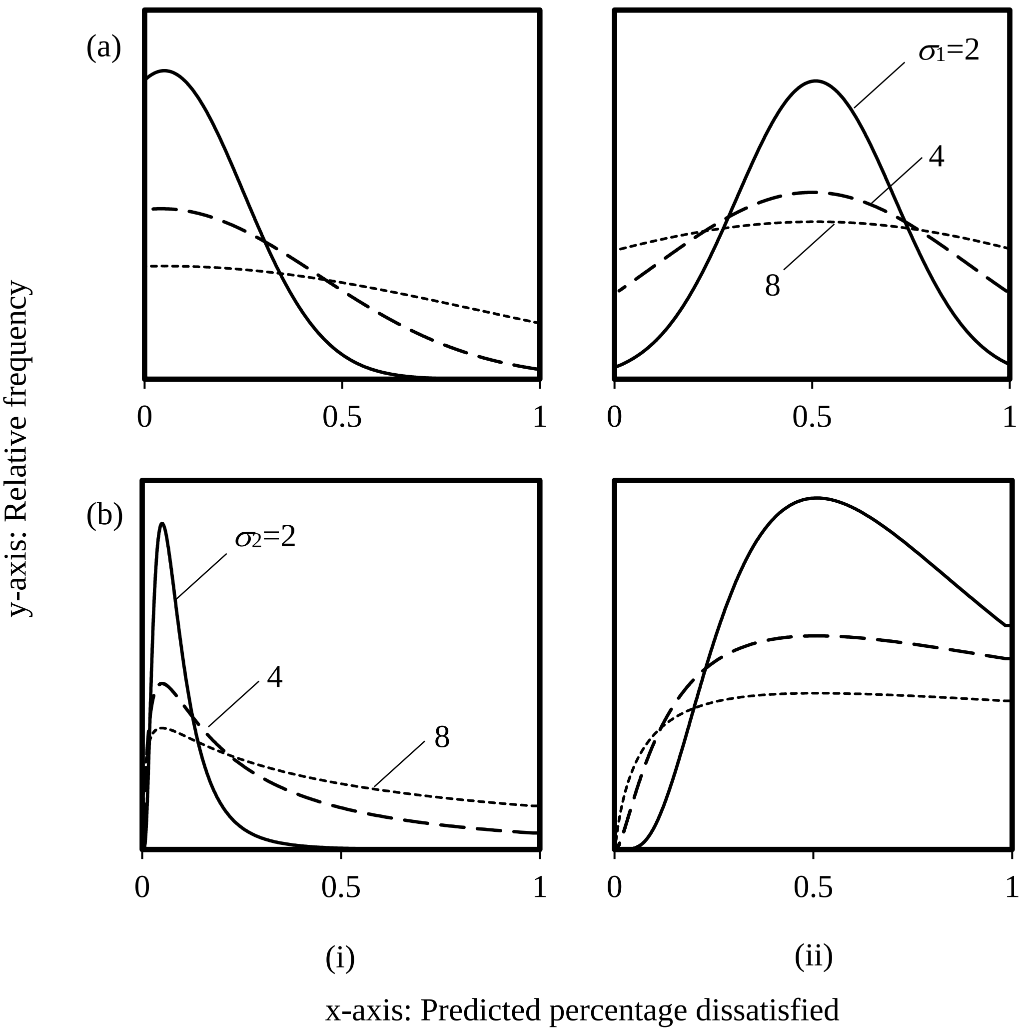

Figure 1. (a) Normal prior distribution function F_1, (b) lognormal normal prior distribution function F_2; (i) *PMV*=0, (ii) *PMV*=±1.5

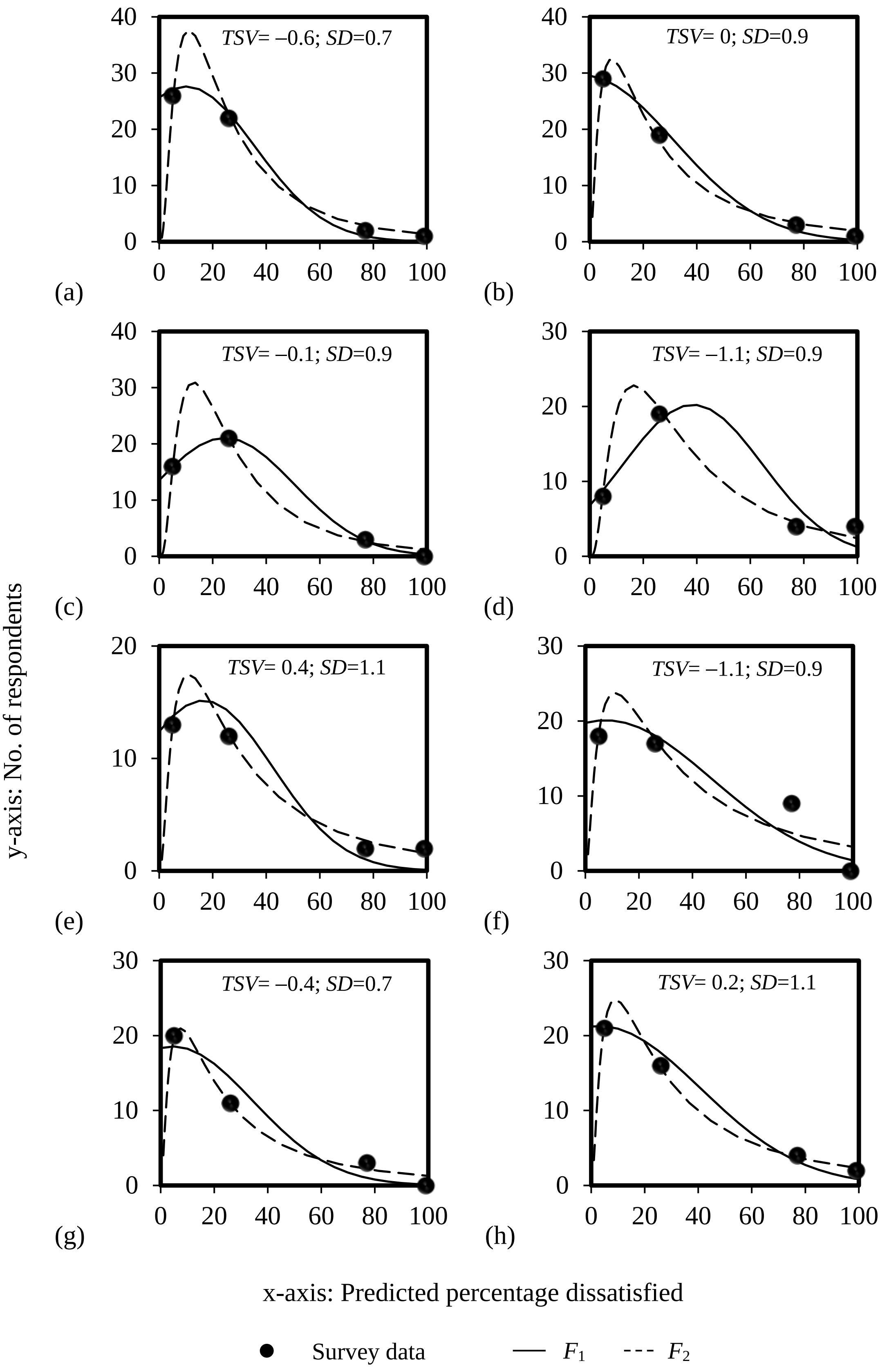

Figure 2. Distribution functions F_1, F_2 for predicted percentage dissatisfied in 8 university teaching rooms

Application of thermal comfort models to predict the percentage dissatisfied in indoor environment becomes a dilemma because adaptation has been shown to be required for various spaces. Although the survey data of percentage dissatisfied determined from the occupant thermal votes (k/n) deviate from the predictions, these cases are limited in sample size and lack generality. Moreover, thermal responses in a general indoor environment of thermal extremes (e.g. $PMV=\pm 3$) are rare and few relevant studies are available. As no conclusive evidence is available, many field model predictions were rejected. However, the deviations observed should not be overlooked.

The question is when to use the percentage dissatisfied k/n or the acceptable error ε, particularly in the cases where significant differences are found between $\bar{\varphi}$ and k/n. The target sample size n_2 can be a parameter that determines the prior distribution function, such that $n=n_2$. With the choice of the prior F, the Bayesian approach gives a posterior median estimate φ' and its error from the observed percentage dissatisfied k/n is given by the following expression,

$$\forall P(A): \left| \varphi' - \frac{k}{n} \right| \leq \varepsilon \qquad \ldots (8)$$

Figure 3 shows the posterior median estimates φ' and the maximum likelihoods for $k/n=0.75$, where the two prior functions $F_{1,2}$ are with distribution shape factors $\sigma_{1,2}=2,8$ for $\bar{\varphi}=0.05$. When $n=4,8,12$, the corresponding errors for F_1 are $-0.39,-0.30,-0.24$ with $\sigma_1=2$ and $-0.10,-0.06,-0.04$ with $\sigma_1=8$, while those for F_2 are $-0.57,-0.36,-0.23$ with $\sigma_2=2$ and $-0.19,-0.10,-0.06$ with $\sigma_2=8$, respectively. The distribution shape factor σ indicates the reliance of the prior estimate and hence how much the posterior estimate is relying on the prior estimate. A smaller σ assumes that a more reliable prior estimate is given, and vice versa.

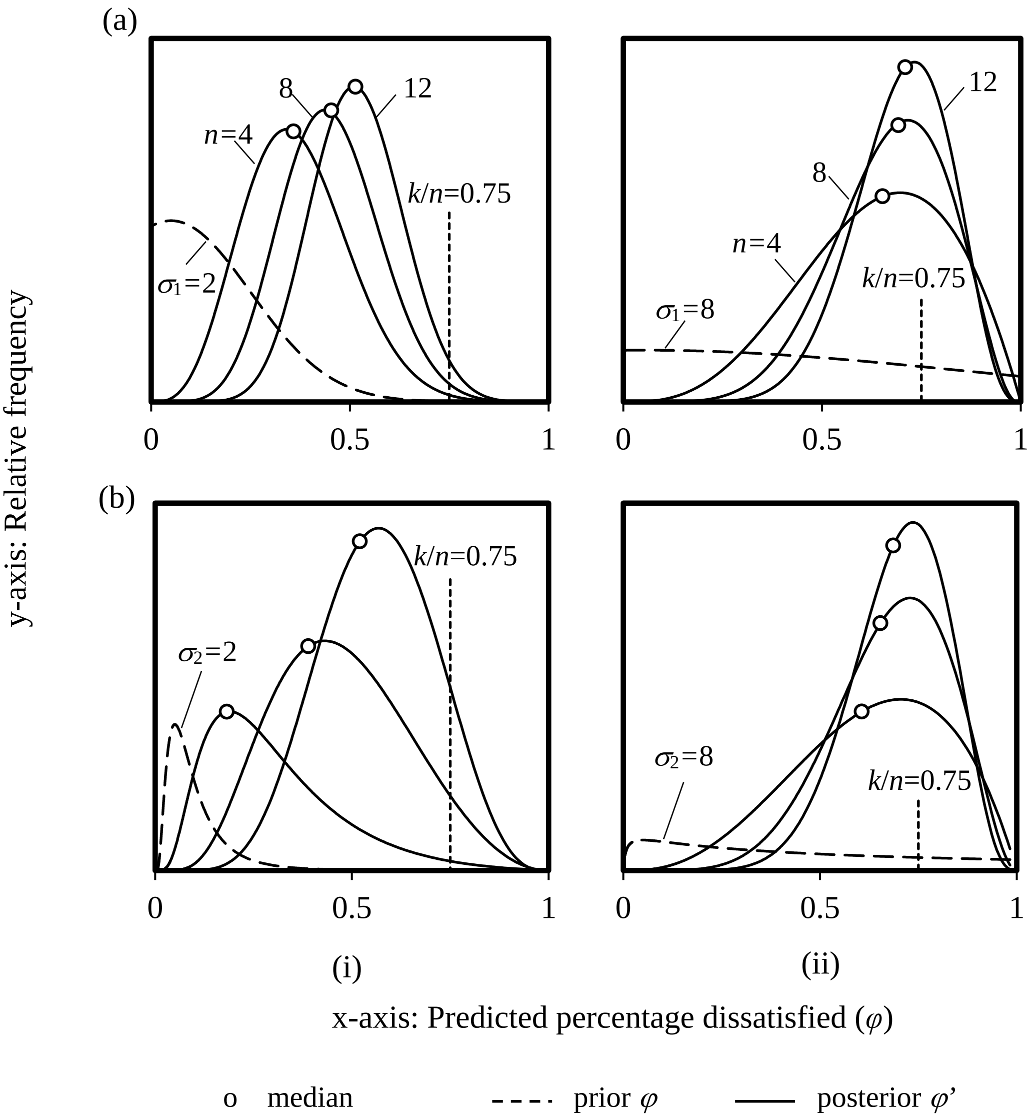

Figure 3. Posterior φ' with k/n=0.75 and PMV=0. Priors (a) F_1, (b) F_2; (i) PMV=0, (ii) PMV=±1.5

Figure 4 exhibits the median posterior estimates φ' when using all $k/n \in [0,1]$ with the two priors for $n \leq 60$ and $PMV \in [0,3]$. The posterior φ' approaches k/n as n increases and that reflects the repeating survey results with large sample sizes may supersede the existing understandings of thermal sensation. A rapid trend of percentage dissatisfied against sample size is reported for cases of larger difference between prior and k/n, indicating a faster response for cases of extreme difference between existing understandings and the new knowledge. Prior function F_1 gives a dip trend initially but more ‘flat’ afterwards. The two priors do not present significant difference for the posterior estimates for large n.

As the shape factor σ is a parameter for measuring the reliance on the new knowledge k/n, the maximum errors ε_{max} for the prior functions are given by an expression below,

$$\forall P(A), \forall k : \varepsilon_{\max} = \max\left(abs\left(\varphi' - \frac{k}{n} \right) \right) \qquad \ldots (9)$$

While the root-mean-square errors ε_{rms} are expressed by,

$$\forall P(A), \forall k : \varepsilon_{rms} = \sqrt{\overline{\left(\varphi' - \frac{k}{n} \right)^2}} \qquad \ldots (10)$$

Figure 5 graphs (a) the maximum errors and (b) the root-mean-square errors for all $P(A)$ and k values with target sample sizes (n) up to 60. These errors correspond to the choice of σ and a target sample size $n \geq n_2$. If a target sample size n_2=1000, then the maximum errors ε_{max} and the root-mean-square errors are 0.009 and 0.004, 0.002 and 0.001, 0.001 and 0.001 for σ=2, 4, 8 respectively.

Hence, with an appropriate choice of shape factor, the Bayesian approach can be applied to cases where the actual sample size does not hit the target sample size. Figure 6 presents a flow diagram illustrating the steps of the Bayesian approach. The procedure was coded in FORTRAN and executed on a personal computer. It can be computed using a worksheet.

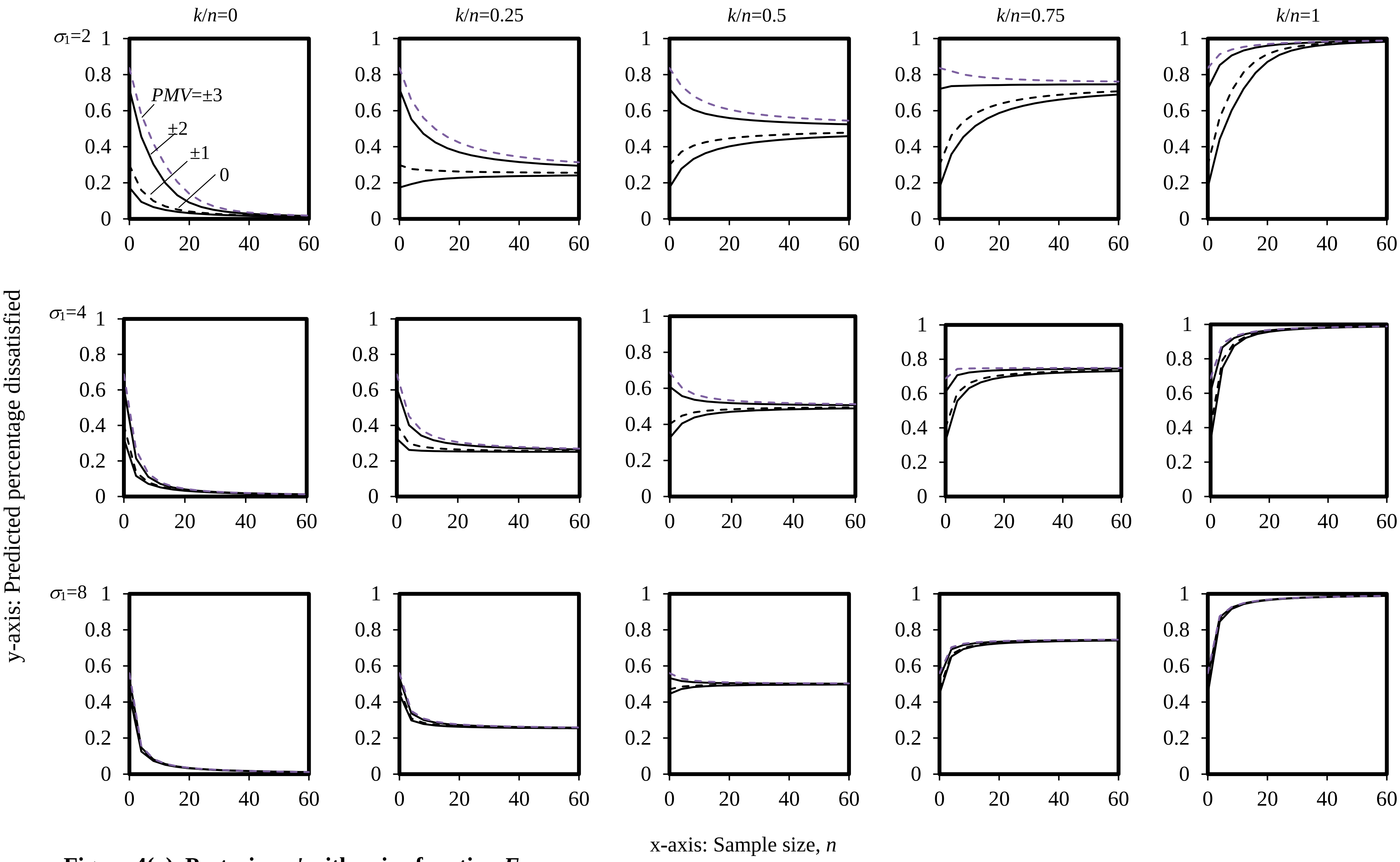

Figure 4(a). Posterior φ' with prior function F_1

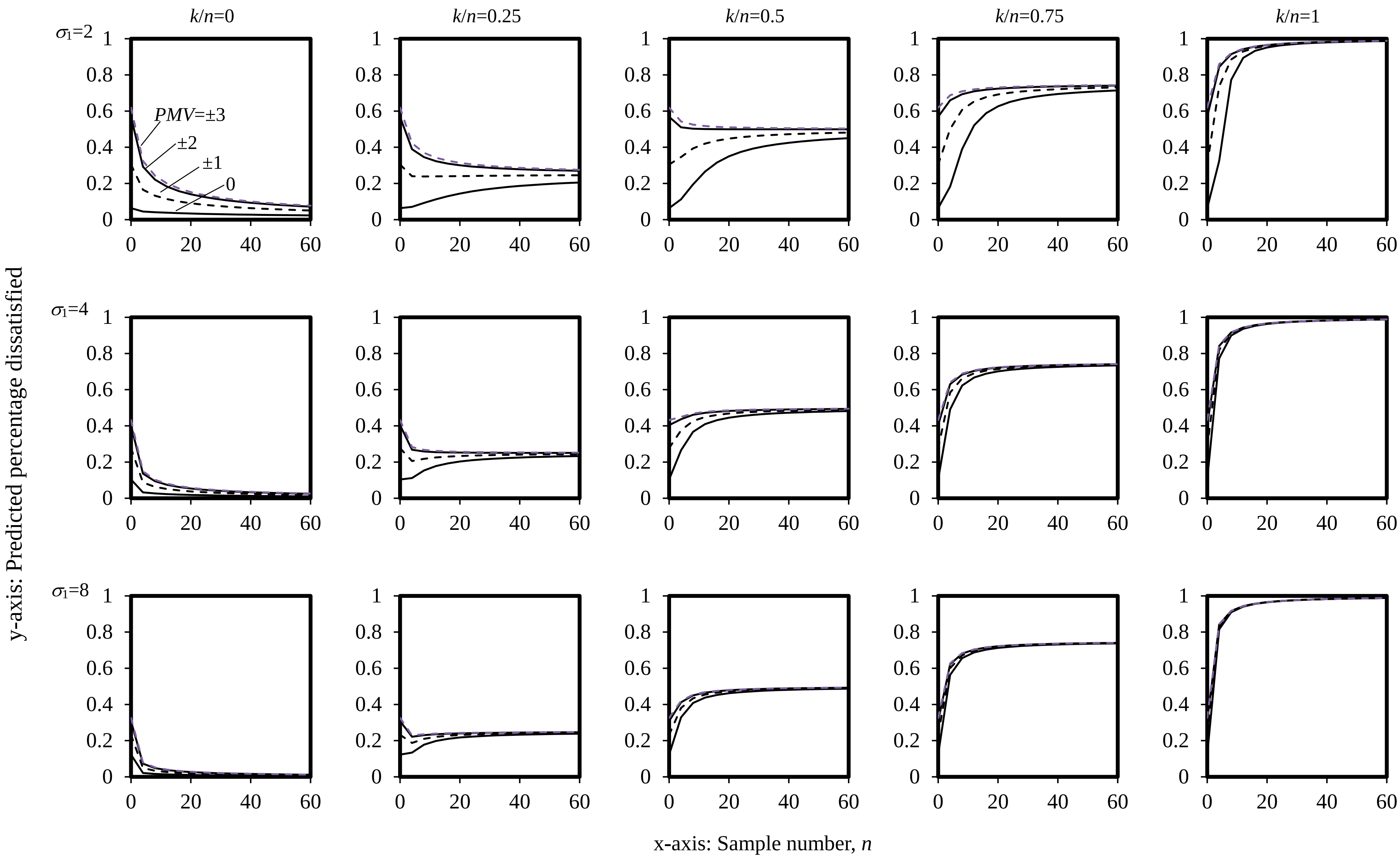

Figure 4(b). Posterior φ' with prior function F_2

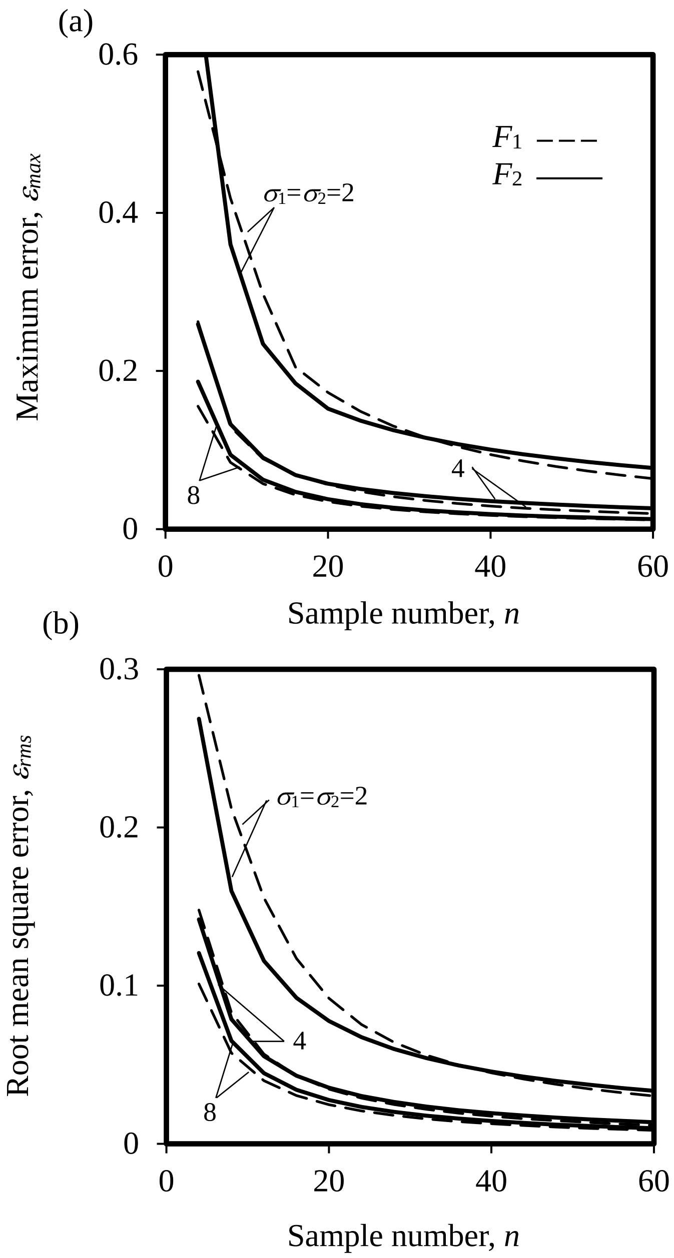

Figure 5. Errors of posterior estimates: (a) maximum, (b) root-mean-square

3. Application examples

Using prior function F_1, the proposed thermal comfort model was applied to some studies as listed in Table 1. Example predictions from both of the model estimates and field survey data are presented in Figure 7. The shape factor was set to 2, corresponding to a target sample size of 1000 for each thermal sensation vote and an acceptable error of 0.1%. The posterior estimates given by the maximum likelihoods lay between the prior estimates and the observed k/n values for surveys of a small sample size n; they are close to the observed values for surveys of a larger sample size.

Figure 8 summarizes the occupant thermal responses against Fanger's *PMV* scale for offices, classrooms, apartments and elderly centres with total sample sizes 1115, 316, 126 and 421 respectively [2, 3, 34]. It groups the predicted mean votes with end bins of ±0.25 for each 0.5 vote. According to the field survey data of occupants' thermal acceptance via a 7-point semantic differential scale (i.e. the full 7-point ASHRAE scale) and a 2-point dichotomous scale (i.e. acceptable or unacceptable), all occupant acceptance votes were considered as a neutral condition to the respondents, while the unacceptance votes as cold and hot feelings the respondents perceived. Very few to no unacceptance votes were recorded in the elderly centres (in a wide *PMV* range); and the vote distribution in apartments was observed different from the ones in offices and classrooms. There was insignificant difference in thermal acceptance/unacceptance votes between offices and classrooms ($p \geq 0.1$, Chi-square test), except for $PMV = -0.5$ and -1 ($p \leq 0.03$, Chi-square test).

The proposed thermal dissatisfaction model with the most demanding settings (a prior function F_1 and a shape factor σ_1=2) was applied to the field tests and the results are graphed in Figure 9. The posterior estimates of thermal dissatisfaction in the *PMV* range of −1.5 to 0.5 agreed very well with the office and classroom survey data when the sample size was large. Otherwise, the estimates were close to the Fanger's predictions, not the *APD*. Even though a number of *PMV* scales with low dissatisfaction rates were observed for apartments, the sample sizes were insufficient and the posterior prediction was similar to Fanger's *PPD*. On the other hand, the large number of thermal acceptances recorded for elderly centres, especially in the *PMV* range of –1.5 to 0.5, gave a flat posterior comparatively. Figure 10 exhibits the values of percentage dissatisfied in terms of feeling 'Cold' or 'Hot' for the locations tested, with a minimum of 5% dissatisfaction assumed, respectively, at positive and negative *PMV* scales. High percentages of acceptance of a cold environment were observed in both classrooms and elderly centres.

Apart from the Fanger's *PMV* model, this study also implemented the newly proposed *PMV-PPD* relationship evaluated from the RP-884 project by Langevin et al. [32] as a prior understanding for the estimation of percentage dissatisfied in air-conditioned offices, air-conditioned classrooms, naturally ventilated apartments and naturally ventilated elderly centres. The results are shown in Figures 11 and 12. As compared with Fanger's *PPD* scale, the RP-884 prior gave smaller values of percentage dissatisfied for extreme votes (i.e. *PMV*=±3) and higher values for a predicted neutral condition (i.e. *PMV*=0). Besides, a smaller *PPD* difference was observed between the posterior and RP-884 prior estimates as compared with the Fanger's prior estimates, especially in the air-conditioned classroom environment.

The primary benefit of the proposed Bayesian approach is that it enables a systematic procedure to update our current beliefs about occupant dissatisfaction with a thermal environment based on the best information available (i.e. predictions made by comfort models and relevant field survey data). The approach evaluates the statistical significance of field measurements and relates the model parameters to the choice of target sample size and acceptable error. It is also useful for making design decisions to build a comfortable thermal environment.

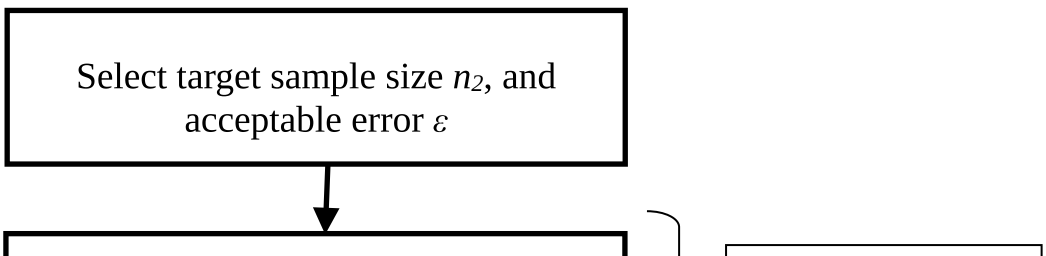

Figure 6. Flow diagram of Bayesian approach

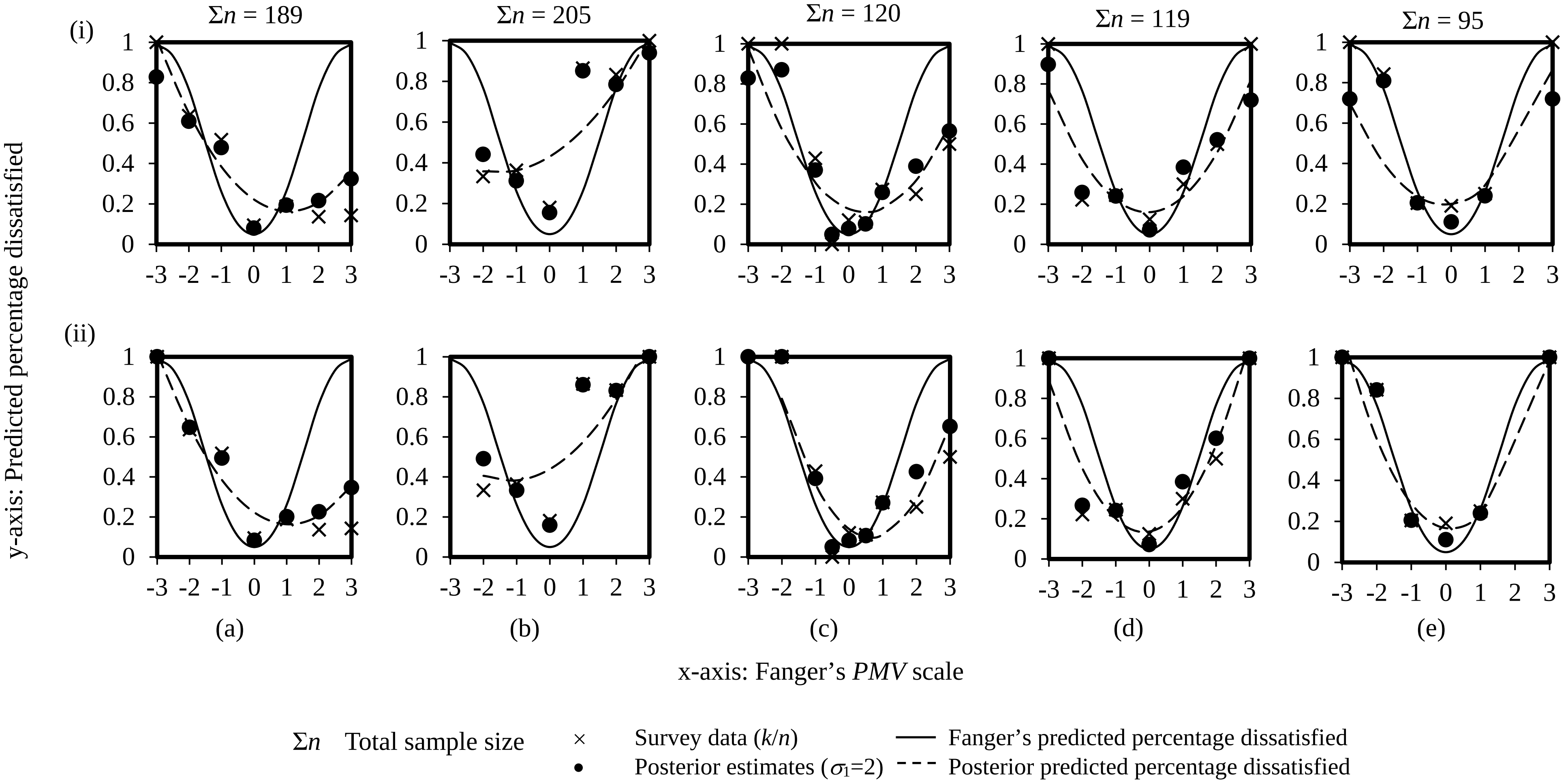

Figure 7. Predicted percentage dissatisfied for residential buildings in (a) Israel (winter), (b) Israel (summer), (c) Harbin, China, (d) Cameroon (Ngaoundere), (e) Cameroon (Kousseri); (i) median, (ii) maximum likelihood

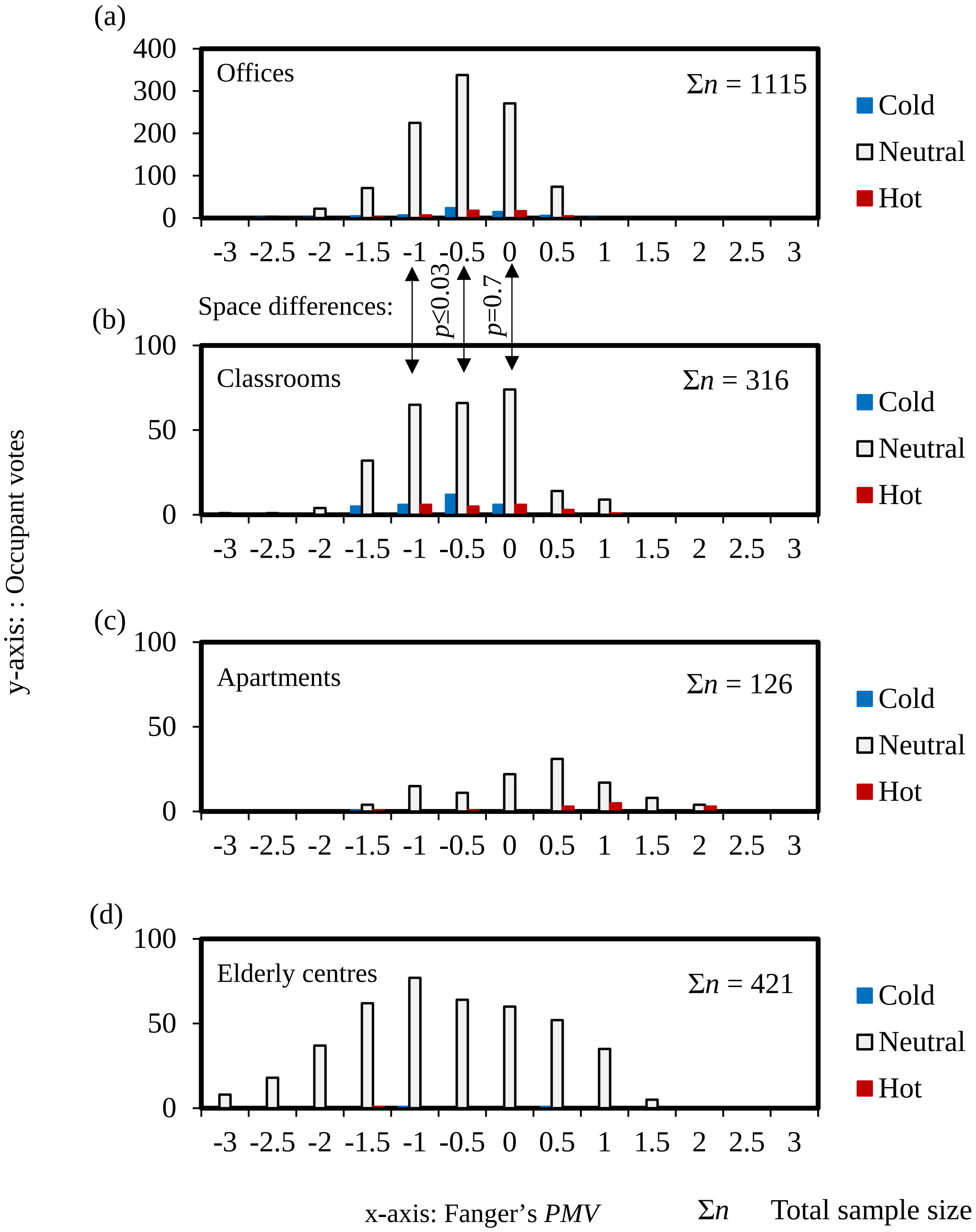

Figure 8. Occupant thermal responses in (a) offices, (b) classrooms, (c) apartments, (d) elderly centres

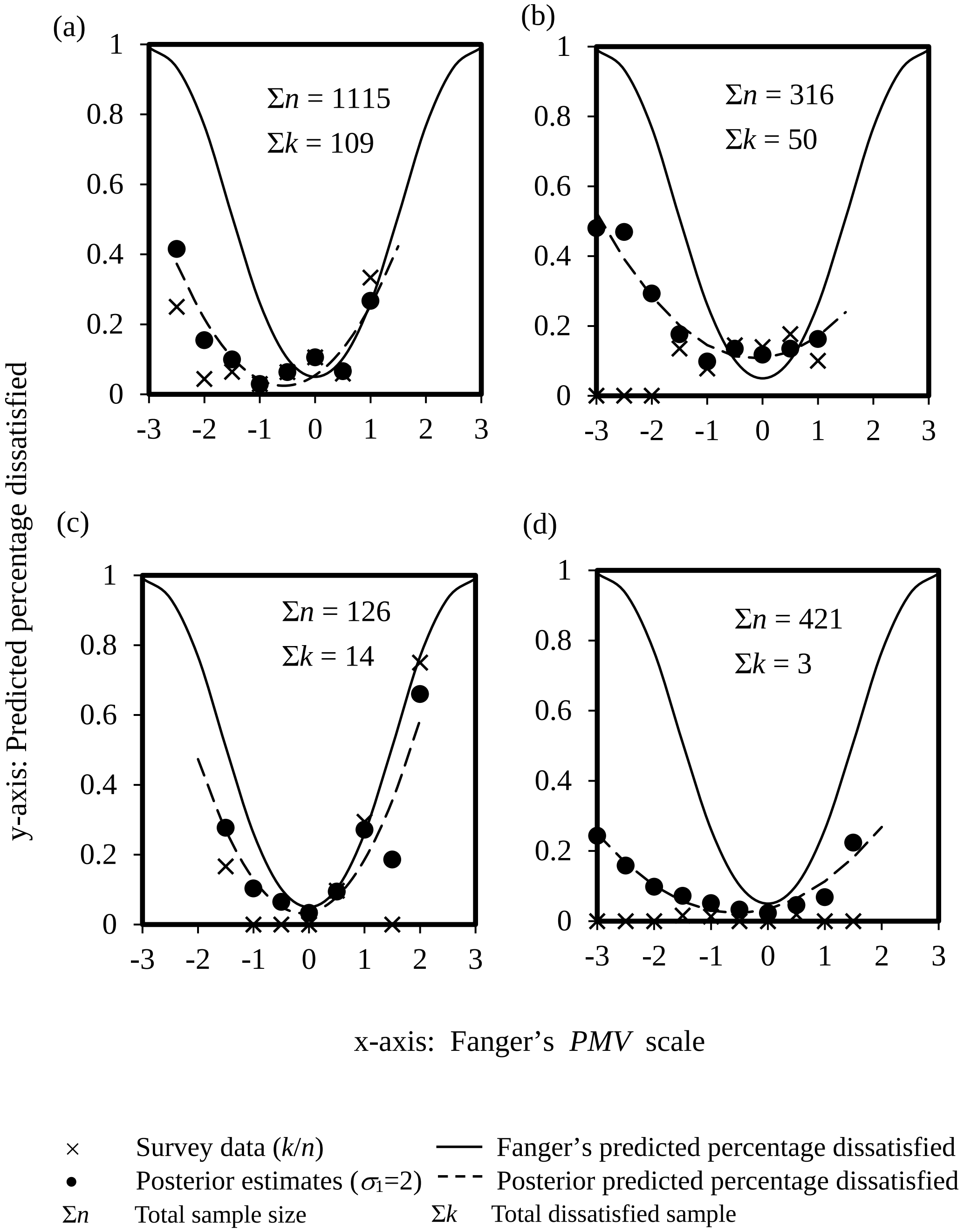

Figure 9. Predicted percentage dissatisfied for (a) offices, (b) classrooms, (c) apartments, (d) elderly centres (Fanger's prior)

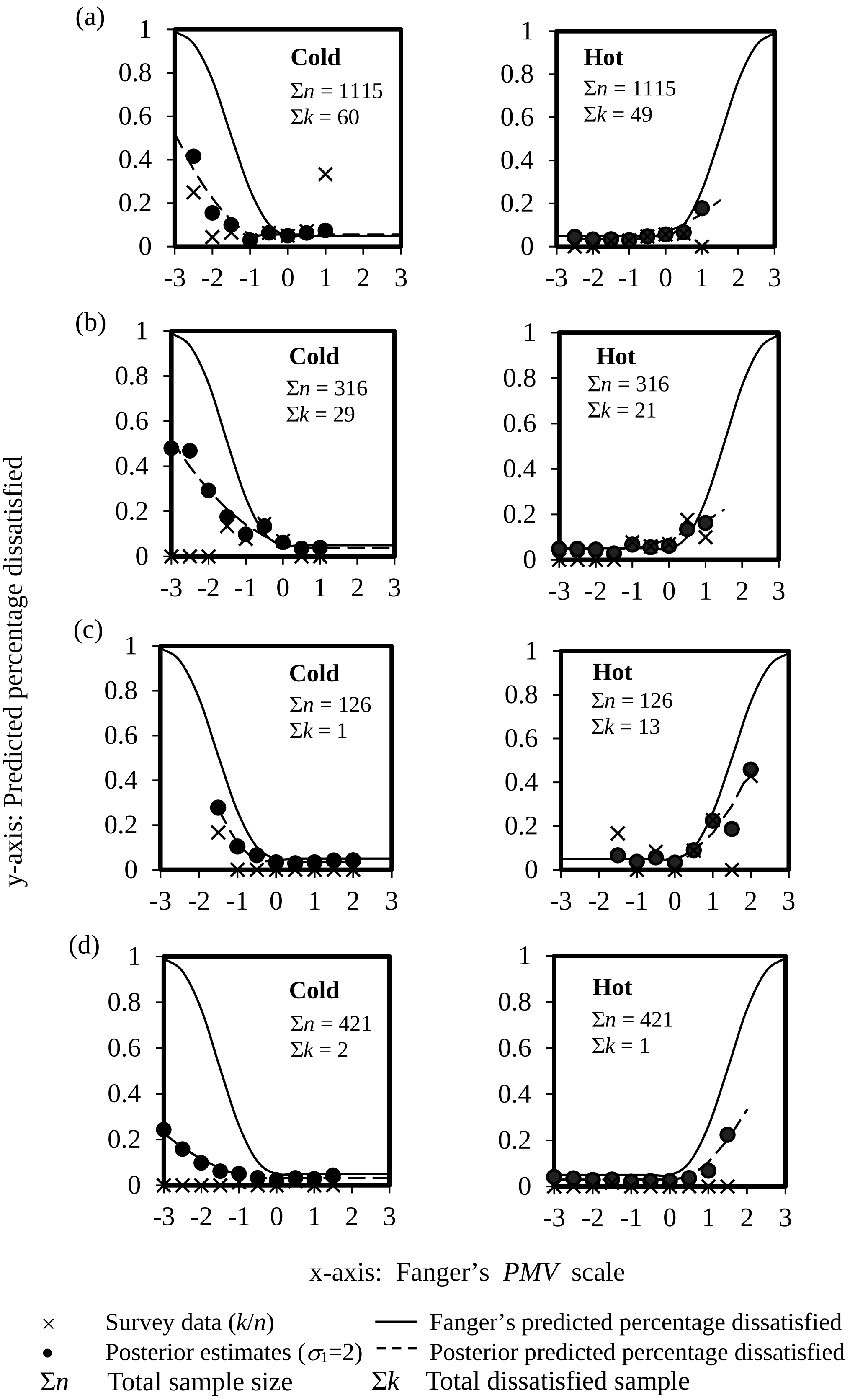

Figure 10. Predicted percentage dissatisfied in terms of feeling 'cold' or 'hot' for (a) offices, (b) classrooms, (c) apartments, (d) elderly centres (Fanger's prior)

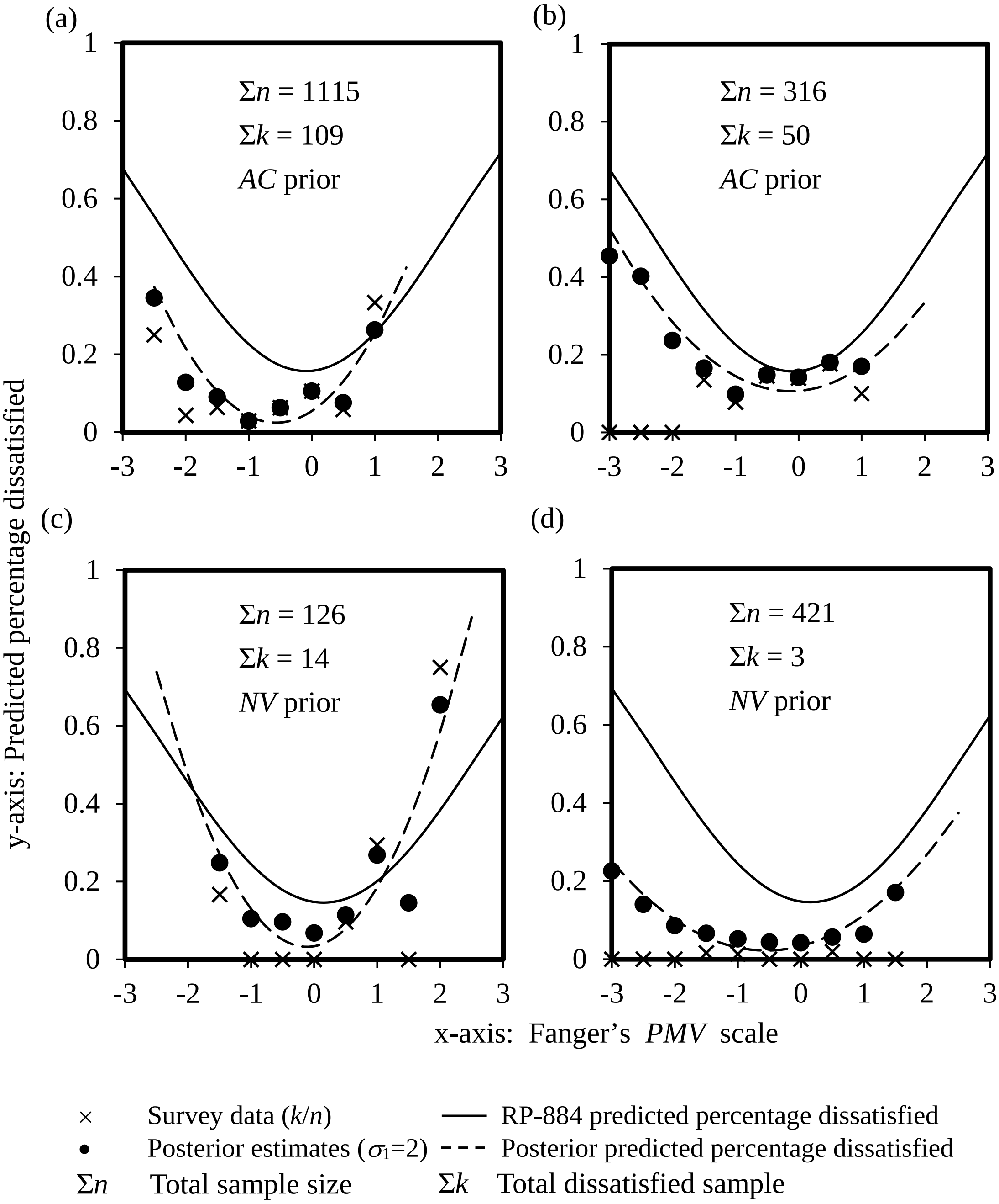

Figure 11. Predicted percentage dissatisfied for (a) offices, (b) classrooms, (c) apartments, (d) elderly centres; (RP-884 prior)

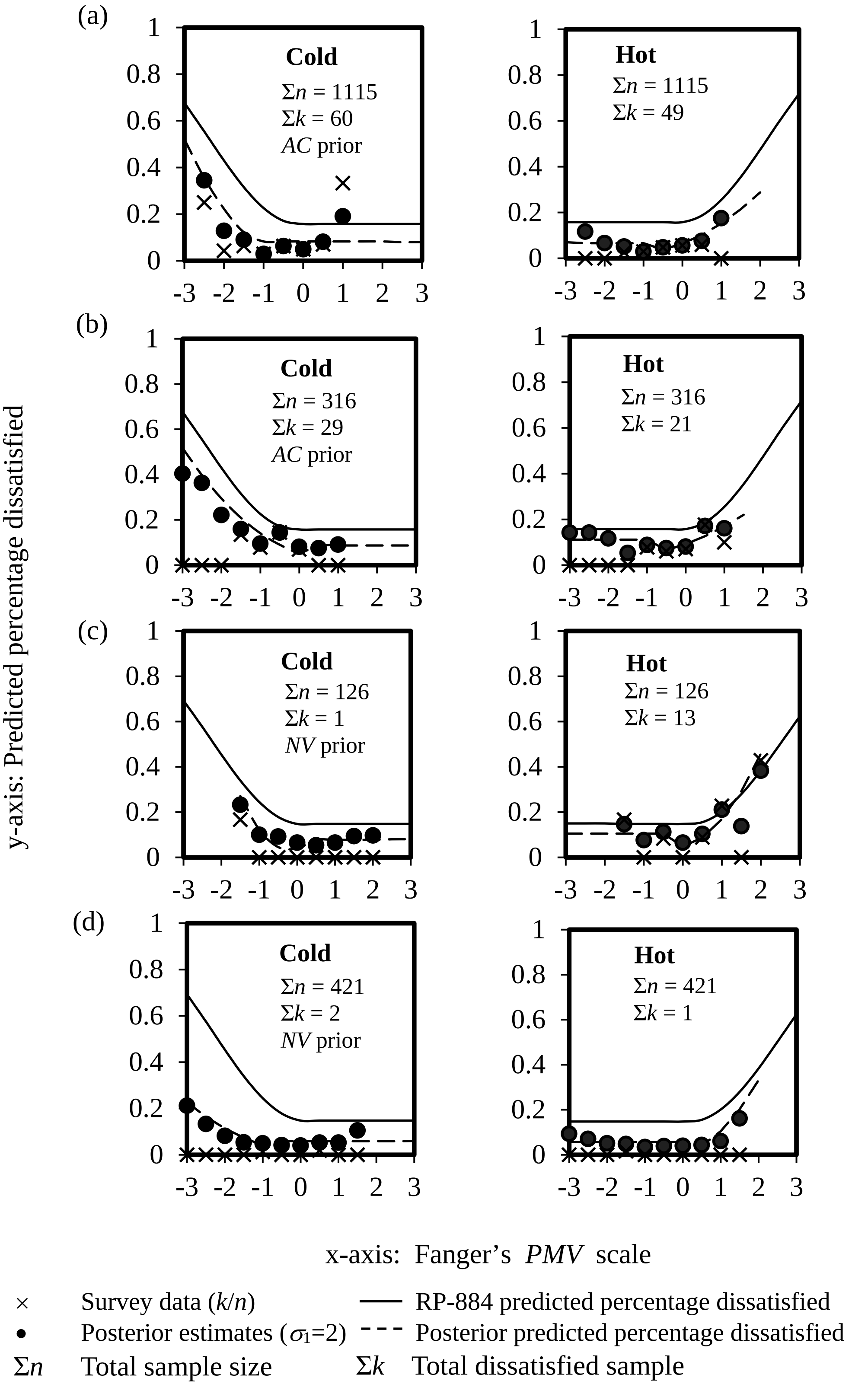

Figure 12. Predicted percentage dissatisfied in terms of feeling 'cold' or 'hot' for (a) offices, (b) classrooms, (c) apartments, (d) elderly centres; (RP-884 prior)

4. Conclusions

Rising numbers of thermal comfort field studies show that Fanger's model is not a good predictor of actual thermal sensation. In addition, statistical significance of field measurements has been questioned and generalized survey results have been ignored in many circumstances. This study proposed a Bayesian approach to update our current beliefs about thermal comfort. Usefulness of the proposed approach was demonstrated through some studies reported in the literature, with a free choice of target sample size. Congruence between Fanger's model prediction and contemporary field survey data was quantified. It showed that the maximum likelihood of posterior estimates was close to the actual percentage dissatisfied (*APD*) obtained from large sample field surveys. For small sample sizes, the Bayesian estimation was close to Fanger's prediction. These findings provide a solution to the choice of thermal comfort criteria in future thermal environment designs.

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