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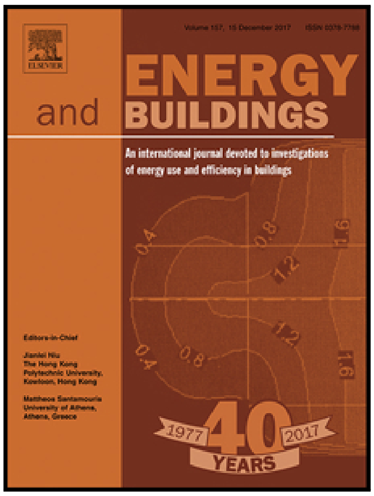

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An Ordered Probability Model for Predicting Outdoor Thermal Comfort

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Abstract:
Outdoor thermal comfort in urban spaces is gaining increasing research attention because it is associated with the quality of life in cities. This paper presents an ordered probability model for predicting the probability distribution of thermal sensation votes (TSVs) based on 1549 observations obtained from a large-scale field survey conducted at a park in Tianjin, China. With a given set of inputs, the developed model can predict the probability that people will feel cold, cool, slightly cool, neutral, slightly warm, warm, or hot. The predictive capability of the ordered probability model was systematically assessed by comparing it with the survey data and a traditional multivariate linear model. Both models had a similar accuracy in predicting single-value TSVs. However, the ordered probability model performed much better than the multivariate linear model in predicting the probability distribution of TSVs. A sensitivity analysis of the ordered probability model revealed that outdoor air temperature was the most important influencing factor. The impacts of global radiation, relative humidity, and activity level on predicted thermal sensation depended on the outdoor air temperature. The developed ordered probability model was used to predict suitable time periods for holding outdoor activities in Tianjin across a whole year. This new model is a more informative tool for predicting outdoor thermal comfort.

Keywords:
Outdoor thermal comfort, Ordered probability model, Thermal sensation vote distribution, Acceptable thermal range, Thermal comfort prediction

1. Introduction

As a result of rapid urbanization in the past half century, 54% of the world's population now lives in cities [1]. Urban outdoor spaces are important because they contribute to the livability and vitality of cities by providing physical, environmental, economic, and social benefits to citizens [2]. Thus, many researchers have proposed that making outdoor spaces attractive to people should be a goal of urban planning and design [3-5]. The thermal comfort of outdoor spaces has been found to be essential in attracting citizens [6-9]. As a result, an increasing number of studies have been conducted during the past two decades to understand outdoor thermal comfort [10-28]. These studies have used physiological thermal comfort models, such as physiologically equivalent temperature (PET) [28,29] and Universal Thermal Climate Index (UTCI) [28,30] to analyze and evaluate thermal comfort in outdoor spaces.

Although these physiological thermal comfort models are valuable tools for investigating outdoor thermal comfort, many researchers have found large discrepancies when applying the models in different regions. For example, Kruger et al. [16] found that the neutral PET in Glasgow, UK differed by 5 K from that in Curitiba, Brazil. Yang et al. [17] discovered that the UTCI range for "no thermal stress" in Umea, Sweden (12 to 17 °C) was much lower than the range in Athens, Greece (17.4 to 24.5 °C) [18]. Many factors, including expectation [19, 20], acclimatization [21, 22], and adaption [23-25], can lead to differences in outdoor thermal comfort between regions. Thus, to consider local features, some studies have developed linear adaptive models for predicting outdoor thermal comfort in particular regions. These linear models express the outdoor thermal sensation as a linear combination of various parameters. For example, Salata et al. [31] developed a linear model called MOCI (Mediterranean Outdoor Comfort Index) to predict the thermal perception of the Mediterranean population by using 1009 observations collected in Rome, Italy. MOCI is a linear combination of air temperature, wind speed, relative humidity, mean radiant temperature, and clothing insulation. Ruiz and Correa [32] developed the "thermal comfort Index for cities of Arid Zones (IAZ)" by linear regression with air temperature, wind speed and relative humidity as predictors. Further linear adaptive outdoor thermal comfort models have been developed by Givoni et al. [33], Nikolopoulou et al. [34], Cheng et al. [35] and Zhao et al. [36].

The linear adaptive models and the physiological models can only provide a single-value prediction of the thermal sensation for a target group of people. For example, linear adaptive models that use the ASHRAE thermal sensation vote (TSV), which is on a seven-point scale (−3 = cold, −2 = cool, −1 = slightly cool, 0 = neutral, 1 = slightly warm, 2 = warm, and 3 = hot), can only provide a single-value TSV for a given condition, e.g., predicted TSV = 0.5. That implies that all of the people in the target group will feel thermally comfortable under the given condition. However, due to individual differences and the large variability in space and time in outdoor thermal environments [37], each person may have his or her own TSV even under the same thermal condition. The TSV for a group of people is thus actually a distribution instead of a single value. In other words, it is more useful to know how many people in the group will feel cold, cool, slightly cool, neutral, slightly warm, warm, and hot, respectively. Such information can better support the decision-making of outdoor activity planners or outdoor space designers by providing probabilities or confidence levels. The idea of predicting probabilities is in line with Fanger's Predicted Percentage of Dissatisfied (PPD) [38] concept, where the PPD is the percentage of "potential complainers" who are dissatisfied with the environment. Therefore, developing a model for predicting the probability distribution of TSV in outdoor environments is worthwhile.

This study developed an ordered probability model for predicting the probability distribution of outdoor thermal comfort based on a database established through a large-scale field survey in a park in Tianjin, China. The performance of the ordered probability model was then systematically assessed by comparing it with the survey data and a traditional multivariate linear model. A sensitivity analysis of the ordered probability model was conducted to identify the major influencing factors. Finally, the developed model was applied to predict suitable time periods for holding outdoor activities at the park across a whole year as a demonstration of the model's application.

2. Methods

This section first briefly presents the traditional multivariate linear model as the baseline model. Then, the ordered probability model used in this study is introduced. Finally, the field data used for developing the outdoor thermal comfort models are briefly described.

2.1 Multivariate linear model

This study used the multivariate linear model as the baseline model because it is widely used in thermal comfort studies. The multivariate linear model takes the following form:

$$TSV_{linear} = \beta_{0,linear} + \beta_{1,linear} x_{1,linear} + \cdots + \beta_{i,linear} x_{i,linear} + \cdots + \beta_{n,linear} x_{n,linear} + \varepsilon_{linear} \quad (1)$$

where TSV_{linear} is the predicted TSV under the given outdoor environment, $x_{i,linear}$ (i from 0 to n) is a predictor variable, $\beta_{i,linear}$ (i from 0 to n) is the coefficient corresponding to the variable $x_{i,linear}$, and ε_{linear} is the random error term. By minimizing the random error term by the least squares method, the coefficients, $\beta_{i,linear}$, can be determined. When determining the final model, it is necessary to exam the significance of each x_i by t-test in order to obtain a statistically sound model. From Eq. (1), we can see that the multivariate linear model can only provide a single-value prediction of TSVs under a given set of predictor inputs.

2.2 Ordered probability model

The ordered probability model [39,40] was originally developed in the field of econometrics and statistics [41]. This study applied the model to predict the probability distribution of TSVs in the outdoor environment. First, an auxiliary variable, z, which represents the sum of the total thermal sensation stimuli, is defined as a linear function:

$$z = \beta_{0,OPM} + \beta_{1,OPM} x_{1,OPM} + \cdots + \beta_{i,OPM} x_{i,OPM} + \cdots + \beta_{n,OPM} x_{n,OPM} + \varepsilon_{OPM} \tag{2}$$

where $x_{i,OPM}$ (i from 0 to n) is a predictor variable that contributes to the total thermal comfort stimuli, such as outdoor air temperature, global radiation, clothing insulation, etc., $\beta_{\iota,OPM}$ (i from 0 to n) is the coefficient corresponding to the variable $x_{i,OPM}$, and ε_{OPM} is a random error term of the total thermal sensation stimuli.

The ASHRAE TSVs (−3 = cold, −2 = cool, −1 = slightly cool, 0 = neutral, 1 = slightly warm, 2 = warm, and 3 = hot) were used in this study. Different levels of z lead to different TSVs, as defined by the following rules:

$$\begin{aligned}
TSV_{OPM} &= -3 \quad if \quad z \le 0 \\
TSV_{OPM} &= -2 \quad if \quad 0 < z \le \alpha_1 \\
TSV_{OPM} &= -1 \quad if \quad \alpha_1 < z \le \alpha_2 \\
TSV_{OPM} &= \ \ 0 \quad if \quad \alpha_2 < z \le \alpha_3 \\
TSV_{OPM} &= \ \ 1 \quad if \quad \alpha_3 < z \le \alpha_4 \\
TSV_{OPM} &= \ \ 2 \quad if \quad \alpha_4 < z \le \alpha_5 \\
TSV_{OPM} &= \ \ 3 \quad if \quad z > \alpha_5
\end{aligned} \tag{3}$$

where α_1 to α_5 are the thresholds for differentiating the TSV groups. All of the $\beta_{\iota,OPM}$ and α_ι values were estimated by minimizing the random error term shown in Eq. (2). With the obtained $\beta_{\iota,OPM}$ and α_ι, the probability density distribution of the thermal sensation stimuli can be assumed to be normally distributed [39]. Therefore, the probability of different TSVs can be calculated by

$$
\begin{aligned}
P(TSV = -3) &= \Phi(-z) \\
P(TSV = -2) &= \Phi(\alpha_1 - z) - \Phi(-z) \\
P(TSV = -1) &= \Phi(\alpha_2 - z) - \Phi(\alpha_1 - z) \\
P(TSV = \ \ 0) &= \Phi(\alpha_3 - z) - \Phi(\alpha_2 - z) \\
P(TSV = \ \ 1) &= \Phi(\alpha_4 - z) - \Phi(\alpha_3 - z) \\
P(TSV = \ \ 2) &= \Phi(\alpha_5 - z) - \Phi(\alpha_4 - z) \\
P(TSV = \ \ 3) &= 1 - \Phi(\alpha_5 - z)
\end{aligned} \tag{4}
$$

where Φ is the cumulative distribution function of the standard normal distribution:

$$\Phi(\mu) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\mu} \exp(-\frac{1}{2} w^2) dw \tag{5}$$

Figure 1 illustrates the probability density distribution of the thermal sensation stimuli. The probability that the target group will vote for a particular TSV can be calculated as the area under the probability density distribution curve in the corresponding thermal sensation stimuli range. For example, the area of the shaded zone shown in Figure 1 is the probability that the target group will vote "neutral" (i.e., TSV = 0). Compared with the multivariate linear model, the ordered probability model can provide richer information about the probability distribution of thermal sensations.

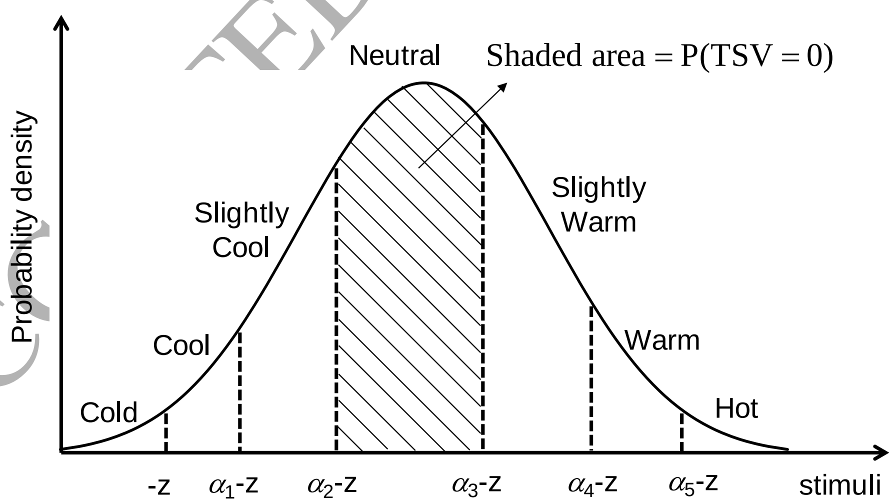
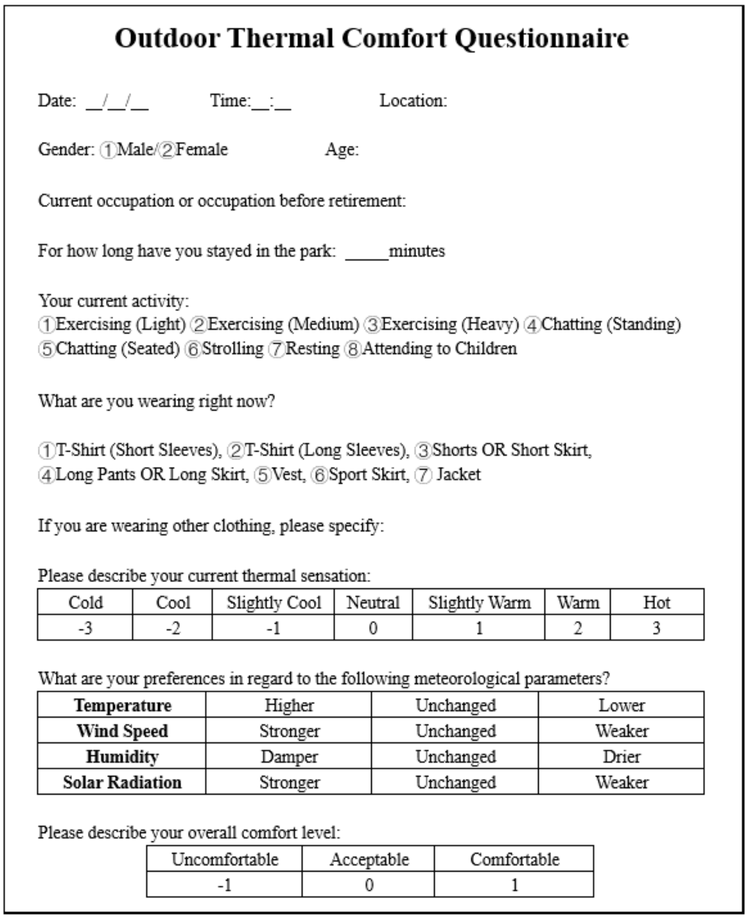


Figure 1. Probability distribution of different TSVs in the ordered probability model.

Both the multivariate linear model and the ordered probability model were established using the commercial statistical software NLOGIT [42].

2.3 Case description

This study used data collected from a large-scale field survey at a park in the center area of Tianjin, China, to develop the outdoor thermal comfort models. The field survey was conducted between 10:00 and 16:00 from March 13, 2012 to January 8, 2013, and involved both questionnaires and microclimate monitoring. The details of the field survey can be found in Lai et al. [43]. This section briefly summarizes the survey methods and statistics. During the survey, the subjects were interviewed in either the open square or the shaded pavilion of the park. Thus, for the microclimate monitoring, we used two micro-weather stations, one in an open square and the other one under a shaded pavilion, to record the outdoor air temperature (T_a), global solar radiation (G), relative humidity (RH), and wind speed (V_a) every 10 minutes at a height of 2 meters above the ground. The questionnaires used in the survey are shown in Figure 2. The first part of the questionnaire was used to obtain personal information such as age, gender, occupation, outdoor exposure time, clothing level, and activity level. The second part collected the subjects' TSVs on the ASHRAE seven-point scale, the preference votes for climatic parameters, and the overall comfort vote. A total of 1549 effective observations, which consists of both the complete answers to the questionnaire and the climatic parameters acquired by the weather stations, were obtained in this study.



Outdoor Thermal Comfort Questionnaire

Date: __/__/__ Time:__:__ Location:

Gender: ①Male/②Female Age:

Current occupation or occupation before retirement:

For how long have you stayed in the park: _____minutes

Your current activity:
①Exercising (Light) ②Exercising (Medium) ③Exercising (Heavy) ④Chatting (Standing)
⑤Chatting (Seated) ⑥Strolling ⑦Resting ⑧Attending to Children

What are you wearing right now?

①T-Shirt (Short Sleeves), ②T-Shirt (Long Sleeves), ③Shorts OR Short Skirt,
④Long Pants OR Long Skirt, ⑤Vest, ⑥Sport Skirt, ⑦ Jacket

If you are wearing other clothing, please specify:

Please describe your current thermal sensation:

Cold	Cool	Slightly Cool	Neutral	Slightly Warm	Warm	Hot
-3	-2	-1	0	1	2	3

What are your preferences in regard to the following meteorological parameters?

Temperature	Higher	Unchanged	Lower
Wind Speed	Stronger	Unchanged	Weaker
Humidity	Damper	Unchanged	Drier
Solar Radiation	Stronger	Unchanged	Weaker

Please describe your overall comfort level:

Uncomfortable	Acceptable	Comfortable
-1	0	1

Figure 2. Questionnaire used in the field survey at a park in Tianjin, China (The original questionnaire was in Chinese).

Table 1 summarizes the statistics of the variables used in the thermal comfort models. Note that, since this study focused on the prediction of TSVs, the preference votes and overall comfort vote were not included in the analysis. Furthermore, it was found that the influence of some parameters, such as occupation and outdoor exposure time, on the TSVs was not significant. Thus, they were also excluded in the analysis. There are two types of the relevant variables: discrete variables and continuous variables. The discrete variables include *TSV*, *GENDER*, *AGE*, and *HOT*. For *TSV*, 674 out of 1549 subjects voted "neutral" (TSV = 0), followed by "hot" (TSV = 3) which was chosen by 330 subjects. The numbers of votes for other TSVs are listed in the table. There were 966 males and 583 females in the survey. The age of the subjects was categorized into three groups: under 30, 30 to 60, and older than 60 years old. Another predictor variable is the "hot day indicator" (*HOT*). In our previous study [43], it was observed that the TSV increased steeply when the outdoor temperature was above 30 °C because the adaptive behavior of the subjects was no longer sufficient to cope with the high temperature. To consider this special scenario, this study included the variable *HOT*, equal to 1 if the temperature was higher than 30 °C, otherwise equal to 0. The continuous variables include activity level (*ACT*), clothing insulation (*CLO*), mean outdoor air temperature (T_a), relative humidity (*RH*), water vapor pressure (P_w), global radiation (*G*), and wind speed (V_a). The activity level of each subject was determined by the metabolic heat generation of his/her corresponding activity type according to the ASHRAE Handbook [44]. The mean ± standard deviation of *ACT* was 112.9 ± 42.1 W. The clothing insulation of each subject was determined by the clothing information provided in the questionnaire according to the ASHRAE Handbook [44]. The mean ± standard deviation of *CLO* was 0.9 ± 0.5 clo. The mean outdoor air temperature, T_a, was 19.0 °C, but the standard deviation was very large, at 12.0 °C. The relative humidity also had a wide range, with a mean *RH* of 43.6% and standard deviation of 19%. The water vapor pressure was determined based on the air temperature and relative humidity; the mean ± standard deviation of P_w was 1.2 ± 1.0 kPa. The mean ± standard deviation of the global radiation (*G*) was 326.2 ± 237.3 W/m^2. The wind speed was generally low with a mean V_a value of 0.5 m/s and standard deviation of 0.4 m/s. That was partially because the park was located in the center area of the city and surrounded by many residential buildings. The surrounding buildings may reduce the wind speed to some extent. Furthermore, when the wind was strong, few people would stay in the park. That resulted in few samples under strong wind conditions. The large standard deviations of the weather variables (T_a, *RH*, *G*) indicate a wide variation in the outdoor thermal environment. That led to a relatively wide variation in TSV. These data were used as the inputs to develop both the multivariate linear model and the ordered probability model for predicting outdoor thermal comfort in Tianjin, China.

Table 1. Descriptive statistics of the survey data.

Variable	Description	Distribution or mean	Minimum/ Maximum	Standard deviation
TSV	Thermal sensation vote: −3/−2/−1/0/1/2/3	31/42/178/674/ 188/106/330	N/A	N/A
GENDER	Male/Female	966/583	N/A	N/A
AGE	<30/30–60/>60	444/384/721	N/A	N/A
HOT	Hot day indicator: 1 if T_a >30 °C, 0 otherwise	298/1251	N/A	N/A
ACT	Activity level (W)	112.9	70/350	42.1
CLO	Clothing (clo)	0.9	0.3/2.2	0.5
T_a	Temperature (°C)	19.9	-5.0/34.5	12.0
RH	Relative humidity (%)	43.6	8.4/71.0	19.0
P_w	Water vapor pressure	1.2	0.1/3.1	1.0
G	Global radiation (W/m^2)	326.2	39.4/865.6	237.3
V_a	Wind speed (m/s)	0.5	0.0/1.5	0.4

3. Results

3.1 Results of the developed models

3.1.1 Multivariate linear model

This study first developed a multivariate linear model as the baseline model using the least squares method. Different combinations of the predictor variables from Table 1 were tested, and those variables with a *p*-value larger than 0.05 were rejected. All of the estimated coefficients, $\beta_{I,linear}$ (*i* from 0 to *n*), were significantly different from zero. The estimated coefficients of the final multivariate linear model are shown in Table 2. The predictor variables included T_a, P_w, *ACT*, *CLO*, and *AGE*. The obtained multivariate linear model is

$$TSV_{linear} = -2.646 + 0.077T_a + 0.708P_w + 0.00159ACT + 0.949CLO - 0.0666AGE \qquad (6)$$

The R^2 value of the model was 0.501. The positive signs of the coefficients for T_a, P_w, *ACT*, and *CLO* indicate that an increase in these variables led to a warmer thermal sensation and vice versa. The negative sign of the coefficient for *AGE* indicates that the elderly subjects felt less warm than the younger subjects due to the reduced metabolic rate of the elderly [45]. Note that the activity level and clothing insulation could be influenced by outdoor air temperature. Interestingly, it was found that the p-value for T_a was relatively high. That may because the *ACT* and *CLO* have partially reflected the influence of T_a on thermal comfort.

Table 2. Multivariate linear model for predicting the TSVs.

Variable	Estimated parameter	p-value
Constant	−2.64600	0.000
T_a	0.07700	0.016
P_w	0.70800	0.000
ACT	0.00159	0.000
CLO	0.94900	0.000
AGE	−0.06660	0.043
R^2	0.50100	

3.1.2 Ordered probability model

As the main objective of this study, an order probability model was developed for predicting the probability distribution of TSVs in Tianjin, China. Again, different combinations of the predictor variables from Table 1 were tested. All of the coefficients $\beta_{\iota,OPM}$ and the thresholds α_ι were estimated by minimizing the random error term shown in Eq. (2). The estimated coefficients of the final ordered probability model are shown in Table 3. The predictor variables included T_a, P_w, G, ACT, and HOT. All of the variables included in the model for the thermal sensation stimuli had a p-value less than 0.05, which means that all of the variables had a significant impact on the thermal sensation stimuli. The obtained ordered probability model is

$$\begin{aligned}
&P(TSV=-3)=\Phi(-z)\\
&P(TSV=-2)=\Phi(0.519-z)-\Phi(-z)\\
&P(TSV=-1)=\Phi(1.470-z)-\Phi(0.519-z)\\
&P(TSV=\ \ 0)=\Phi(3.200-z)-\Phi(1.470-z)\\
&P(TSV=\ \ 1)=\Phi(3.732-z)-\Phi(3.200-z)\\
&P(TSV=\ \ 2)=\Phi(4.138-z)-\Phi(\alpha 3.732-z)\\
&P(TSV=\ \ 3)=1-\Phi(4.138-z)\\
&\textit{where}\\
&z=1.117+0.0505T_a+0.101P_w+0.00044G+0.0020ACT+1.683HOT
\end{aligned} \tag{7}$$

Table 3. Ordered probability model for predicting the TSVs.

Independent variable	Estimated parameter	*p*-value
Constant	1.11700	0.000
T_a	0.05050	0.000
P_w	0.10100	0.009
G	0.00044	0.006
ACT	0.00200	0.003
HOT	1.68300	0.000
α_1	0.51900	0.000
α_2	1.47000	0.000
α_3	3.20000	0.000
α_4	3.73200	0.000
α_5	4.13800	0.000
R^2	0.54300	

From the model, it can be seen that an increase in T_a, P_w, G, and ACT will result in increased thermal sensation stimuli, z. That will shift the thermal sensation distribution to the “hot side,” as shown in Figure 3. That is, the increased thermal sensation stimuli, z, will lead to an increase in the probability that the target people will feel hot. In contrast, a decrease in those variables will shift the distribution to the “cold side,” which means that the probability that people will feel cold will increase. Furthermore, the positive sign of the coefficient for the “hot day indicator” indicates that more subjects voted for “hot” (TSV = 3) when the outdoor air temperature was greater than 30 °C. All of the above findings correspond to people’s intuition that greater outdoor air temperature, global radiation, and activity level will lead to a warmer thermal sensation. The wind speed (V_a) measured in this study was generally less than 1 m/s and did not show a wide variation. As a result, it was not a significant parameter in the developed ordered probability model.

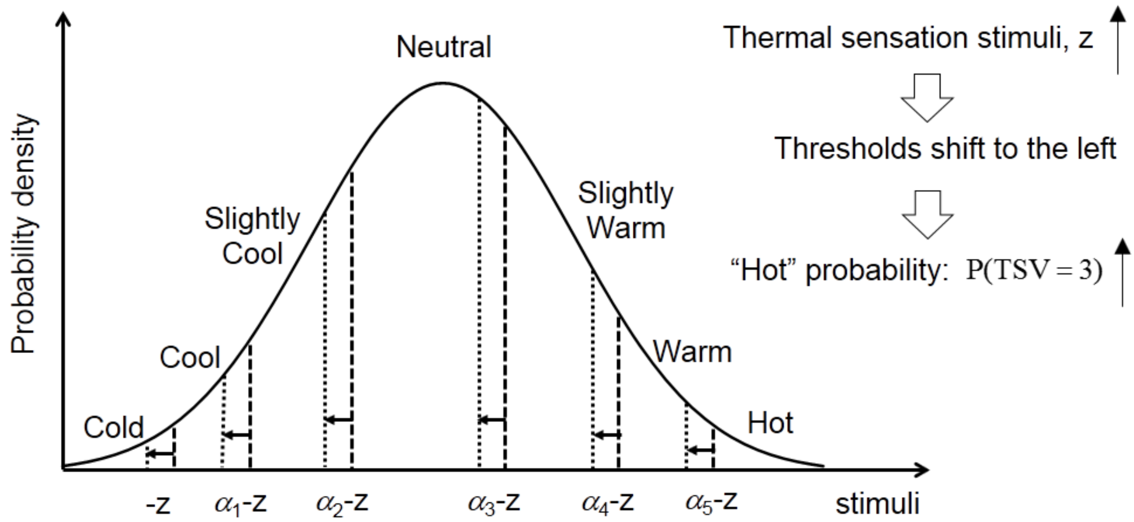


Figure 3. Changes in the probabilities of the different TSVs with increased thermal sensation stimuli.

3.2 Comparison of the predictive capability of the models

This study systematically assessed the predictive capability of the ordered probability model by comparing it with the survey data and the traditional multivariate linear model. These two models are quite different in nature. The multivariate linear model provides a continuous single-value prediction of TSV, while the ordered probability model predicts the probability distribution of the seven discrete TSVs. To compare the models, the distribution obtained from the ordered probability model was first converted to the expected TSV (a single value) for each of the 1549 observations. The accuracy of predicting the single-value TSV for each subject was then compared for the two models, as detailed in sub-section 3.2.1. Next, the continuous single-value TSVs from the multivariate linear model were converted to discrete TSVs on the seven-point scale. The global distribution of the discrete TSVs for the 1549 observations was then established for both models and compared with the survey data, as detailed in sub-section 3.2.2. Finally, this study focused on the two models' prediction of TSV probabilities under a given condition and compared them with the survey data, as detailed in sub-section 3.2.3.

3.2.1 Comparison of the single-value TSV for each subject

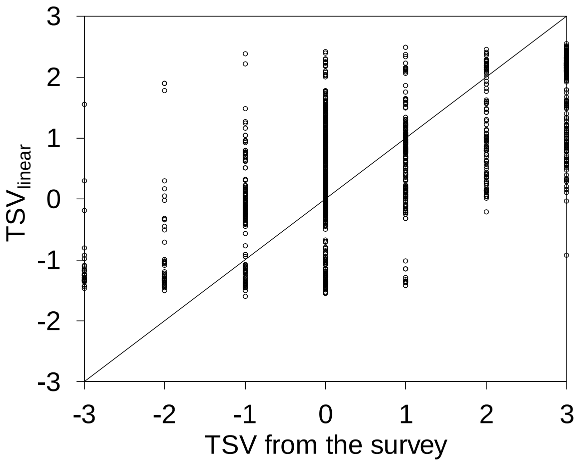
For each of the 1549 observations, the multivariate linear model predicted a continuous TSV using Eq. (6) with the corresponding inputs. The order probability model provided a probability distribution of the seven discrete TSVs using Eq. (7). To compare the results of the models, first, the expected TSV for each subject based on the probability distribution obtained from the ordered probability model was calculated:

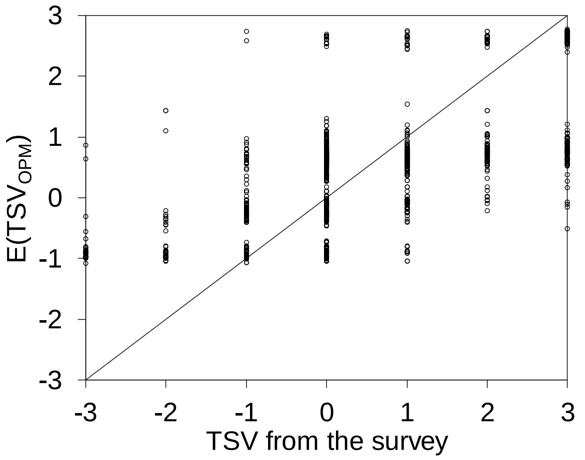
$$E(TSV_{OPM}) = \sum_{N=-3}^{N=3} [N \times P(TSV = N)] \qquad (8)$$

Therefore, for each of the 1549 observations, the predicted single-value TSV could be obtained for the ordered probability model. Figure 4(a) compares the predicted TSV from the multivariate linear model with the survey data, while Figure 4(b) compares the predicted $E(TSV_{OPM})$ from the ordered probability model with the survey results. It can be seen that, in general, the two models had similar accuracy on a single-value prediction basis. To further quantitatively compare their accuracy, the R^2 of the ordered probability model based on predicting the $E(TSV_{OPM})$ was calculated by

$$R^2_{OPM} = 1 - \frac{\sum_{j=1}^{m} (TSV_j - E(TSV_{j,OPM}))^2}{\sum_{j=1}^{m} (TSV_j - \overline{TSV})^2} \qquad (9)$$

where j denotes an observation, m is the total number of observations, and $\overline{TSV}$ is the mean value of the observed TSVs. The R^2_{OPM} of the ordered probability model was 0.543, slightly higher than that of the multivariate linear model (0.501). The two models had a similar accuracy for predicting a single-value TSV.





(a) (b)

Figure 4. Comparison of the TSV survey data and (a) the predicted TSV from the multivariate linear model and (b) the predicted expectation of TSV from the ordered probability model.

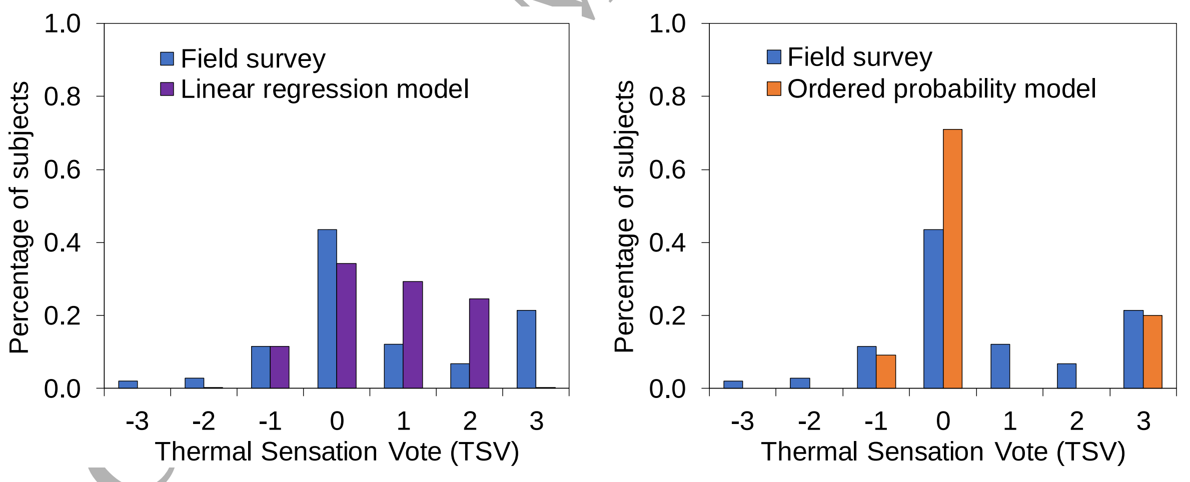
3.2.2 Comparison of the global TSV distribution for the 1549 observations

In addition to the prediction of a single-value TSV for each subject, it is worthwhile to further compare the capability of the two models in predicting the global TSV distribution for the 1549 observations, using the survey data as the benchmark. The global TSV distribution means the percentages of the 1549 subjects who would vote for each seven-point TSV. For the ordered probability model, first, we assumed that the subject would vote for the TSV with the highest predicted probability. For example, if the predicted probability distribution of TSVs for a subject was 8.6%, 11.6%, 35.4%, 41.6%, 2.1%, 0.5%, and 0.2% for "cold" (−3), "cool" (−2), "slightly cool" (−1), "neutral" (0), "slightly warm" (1), "warm" (2), and "hot" (3), respectively, we considered that this subject would vote for "neutral" (0), because its probability was the highest. By doing this for all 1549 subjects, the number of subjects who would vote for each TSV can be determined. Then, the predicted global TSV distribution can be determined for the ordered probability model. For the multivariate linear model, the predicted TSV is not necessarily an integer on the seven-point scale. Therefore, the predicted continuous TSVs were converted to discrete TSVs according to the cutoffs shown in Table 4. For example, if the TSV predicted by the multivariate linear model was 0.12, we considered that this subject would vote for "neutral" (0), because 0.12 is within the range of −0.5 to 0.5. Again, by doing this for all 1549 subjects, the number of subjects who would vote for each seven-point TSV can be determined for the multivariate linear model. Note that the continuous-discrete TSV conversion was solely for the sake of comparison in terms of predicting the global TSV distribution.

Table 4. Conversion of the predicted continuous TSVs by the multivariate linear model to discrete TSVs on the seven-point scale

Predicted continuous TSV by multivariate linear model	Discrete TSV
<−2.5	Cold (−3)
−2.5 to −1.5	Cool (−2)
−1.5 to −0.5	Slightly cool (1)
−0.5 to 0.5	Neutral (0)
0.5 to 1.5	Slightly warm (1)
1.5 to 2.5	Warm (2)
>2.5	Hot (3)

Figure 5(a) compares the global TSV distribution for the 1549 observations from the survey with the multivariate linear model. The global TSV distribution from the field survey shows that the majority of the cases were “neutral” (0), while a considerable proportion of the cases were “hot” (3). However, the multivariate linear model overestimated the “slightly warm” (1) and “warm” (2) sensations, and significantly underestimated the “hot” (3) sensation. Figure 5(b) compares the global TSV distribution for the 1549 observations from the survey with the ordered probability model. The results show that the ordered probability model better reflects the global TSV distribution by satisfactorily predicting the percentage of “hot” (3) cases. However, the ordered probability model missed the “slightly warm” and “warm” votes.



(a) (b)

Figure 5. Comparison of the surveyed and predicted global TSV distributions: (a) the multivariate linear model and (b) the ordered probability model.

Note that the global TSV distribution from the ordered probability model shown in Figure 5(b) was based on the assumption that the subject would vote for the TSV with the highest predicted probability. However, this assumption may not fully reflect the actual situation. For example, if the predicted probabilities of “neutral” (0) and “slightly warm” (1) are 51% and

49%, respectively, "neutral" will be chosen according to the highest probability assumption. Nevertheless, it is almost equally likely that this subject will vote for "slightly warm." To overcome this problem, this study used another method to calculate the global TSV distribution for the ordered probability model. For each discrete TSV, the average of the predicted probability over the 1549 subjects was calculated as follows:

$$P_{global}(TSV = N) = \frac{\sum_{j=1}^{m} P_j(TSV = N)}{m}, \quad N = -3\ to\ 3$$

(10)

where j denotes an observation and m is the total number of observations. Namely, Eq. (10) took the average of the predicted probabilities over the 1549 subjects for each seven-point TSV. Then, this averaged value was regarded as the percentage of subjects who would vote for this TSV. Figure 6 shows the global TSV distribution calculated by Eq. (10) and compares it with the actual global TSV distribution from the survey. A good match was found. For example, the percentage of subjects who voted for "neutral" (0) in the survey was 43.6%, while the prediction from the ordered probability model (Eq. (10)) was 42.2%, a difference of only 1.4 %. The percentage of subjects who voted for "hot" (3) was 21.3% in the survey and 21.9 % in the model. Therefore, with Eq. (10), the ordered probability model can accurately predict the global TSV distribution for the 1549 observations.

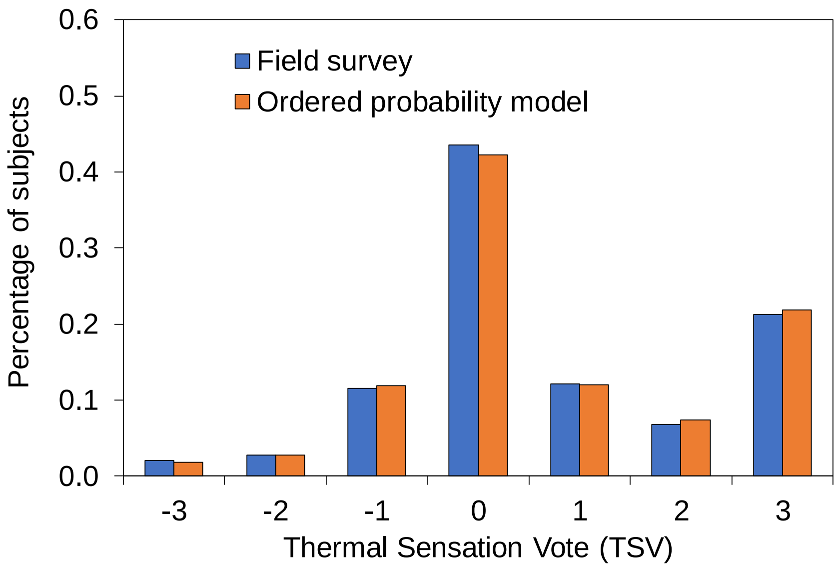


Figure 6. Comparison of the global TSV distribution for the 1549 observations from the survey and the ordered probability model (Eq. (10)).

3.2.3 Comparison of the TSV probabilities under a given condition

In practical applications, such as when making decisions about whether to hold an outdoor event or not, it is crucial to predict the percentage of the target people who will be satisfied with a given outdoor thermal condition. Therefore, this study further compared the predictive capability of the ordered probability model with the multivariate linear model in terms of predicting the TSV probabilities under a given condition. Figure 7 compares the predicted probabilities of each TSV under an actual condition where T_a = 28.5 °C, RH = 50% (P_w = 1.78kPa), G = 218.5 W/m^2, CLO = 0.95 clo, and ACT = 126.6 W. The central three TSVs ("slightly cool," "neutral," and "slightly warm") are considered thermally acceptable in some outdoor and indoor thermal comfort studies [46-49]. From the survey, the total percentage of subjects who voted for the central three TSVs was 68.2% according to the 44 observations available under this certain condition. That is, more than two thirds of the people considered this particular outdoor thermal condition to be acceptable. However, under this condition, the multivariate linear model predicted the TSV to be 2.1, corresponding to "warm" (+2) according to Table 4. Therefore, the multivariate linear model failed to predict that most of the subjects felt thermally acceptable under this condition. In this case, the results from the multivariate linear model may lead to the erroneous conclusion that the particular outdoor thermal condition is unfavorable for holding an outdoor activity. In contrast, the predicted probability for the central three TSVs from the ordered probability model was 73.1%. Thus, the model correctly predicted that most of the subjects felt thermally acceptable under this condition. Therefore, the ordered probability model can provide a more realistic estimation of the thermal sensations among a group of people than the multivariate linear model.

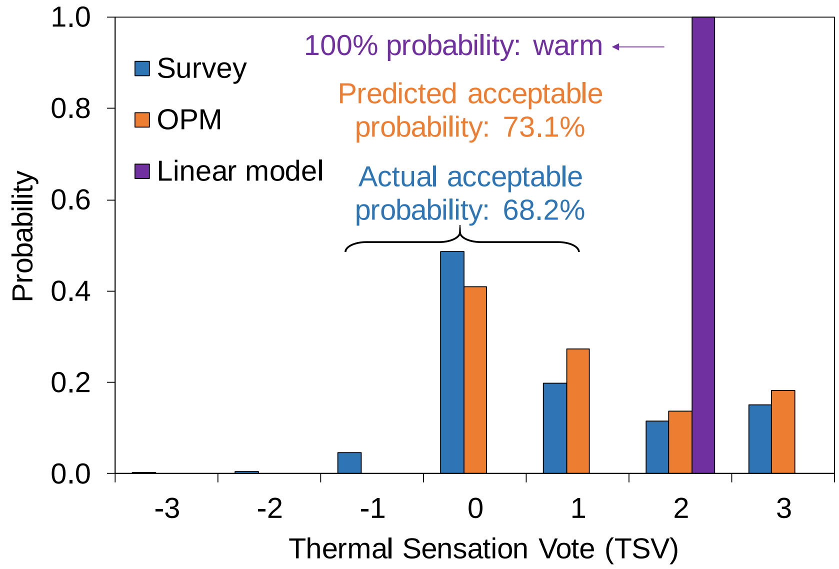


Figure 7. Comparison of the survey results with the predicted TSV probabilities from the ordered probability model and multivariate linear model under the condition T_a = 28.5°C, RH = 50% (P_w = 1.78 kPa), G = 218.5 W/m^2, CLO = 0.95 clo, and ACT = 126.6 W.

To further validate the ordered probability model, the predicted probabilities of the central three TSVs were compared with the survey data for different outdoor air temperatures. The central three TSVs were defined as the satisfied votes by Fanger [38] or as acceptable votes by several outdoor thermal comfort researches [18, 46, 47]. Figure 8 shows the probability of the central three TSVs from the survey and the ordered probability model when the outdoor air temperature was from −5 to 36 °C, which was the actual range of the outdoor air temperature in the field survey. The bars for the survey probabilities were obtained by adding up the central three TSVs for every 3 °C of outdoor air temperature interval. The model prediction of the probability of the central three TSVs is shown as a line. The comparison shows that the model satisfactorily predicted the variation in the probabilities of the central three TSVs at different outdoor air temperatures. For example, when the outdoor air temperature was 25 °C, the ordered probability model predicted that 77.3% of the subjects would feel thermally acceptable. That matched very well with the survey result that 82.8% of the subjects felt acceptable at this temperature. When the outdoor air temperature was 10°C, the ordered probability model predicted that 89.1% of the subjects would feel thermally acceptable. That again matched very well with the survey result that 94.2 % of the subjects felt acceptable. It is worth noting that when the outdoor temperature is over 30 °C, the probability of acceptable thermal comfort significantly decreases. This phenomenon was also successfully captured by the ordered probability model.

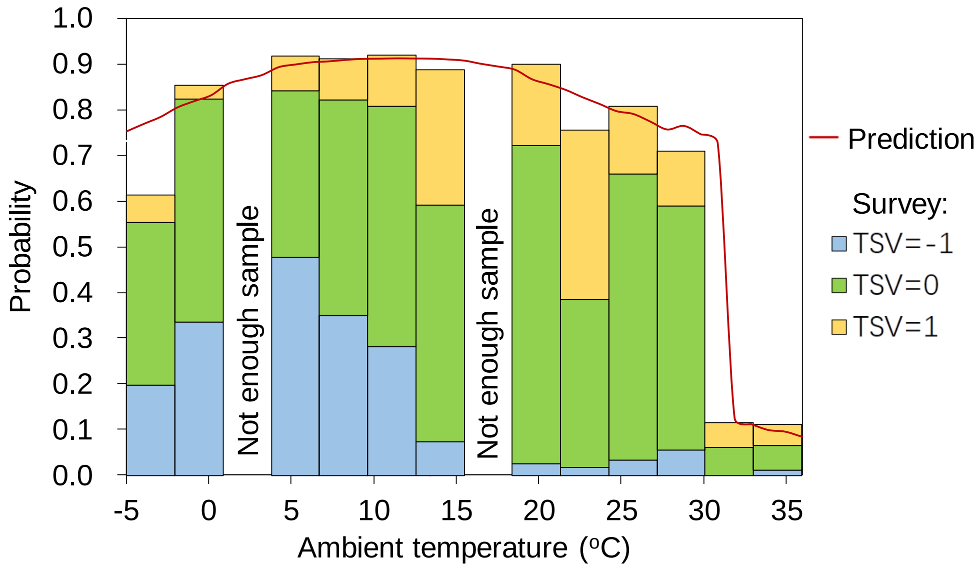


Figure 8. Comparison of the predicted probabilities of the central three TSVs from the ordered probability model with the survey data at different outdoor air temperatures.

The above comparisons show that the ordered probability model has a similar accuracy in predicting the single-value TSV for each subject compared with the multivariate linear model. However, the ordered probability model performed much better than the multivariate linear model in predicting the global TSV distribution for the 1549 observations and the TSV probabilities under a given condition. As the decision on whether an outdoor activity should be held greatly depends on the probability that the target group of people will feel thermally acceptable/comfortable, we recommend the ordered probability model for predicting outdoor thermal comfort.

3.3 Analysis of the influencing factors in the ordered probability model

The previous section demonstrated the predictive capability of the ordered probability model. To further show the advantage of the model, this investigation used the developed model, i.e. Eq. (7), to analyze the influencing factors, including the outdoor air temperature, relative humidity, global solar radiation, and activity level, on the outdoor thermal comfort in Tianjin. First, three probabilities, namely cool discomfort probability (*CDP*), comfort probability (*CP*), and warm discomfort probability (*WDP*), were defined as follows:

$$\begin{aligned} CDP &= P(TSV = -3, -2) \\ CP &= P(TSV = -1, 0, 1) \\ WDP &= P(TSV = 2, 3) \end{aligned} \tag{11}$$

CDP is the sum of the probabilities of cold (−3) and cool (−2) TSVs, *CP* is the sum of the probabilities of the central three TSVs (slightly cool (−1), neutral (0), and slightly warm (1)), and *WDP* is the sum of the probabilities of warm (2) and hot (3) TSVs. These definitions are in accordance with the assumption that the central three TSVs are within the “neutral comfort zone” [44-47]. *CDP*, *CP*, and *WDP* are useful thermal comfort indices to help outdoor event organizers to decide whether an outdoor activity should be held or not.

Table 5 shows the case setup for the analysis of the influencing factors. First, the influence of outdoor air temperature (T_a) was assessed by setting global radiation (*G*) and activity level (*ACT*) at the mean values from the field survey. The relative humidity (*RH*) was set at 50%. The influence of *G*, *RH*, and *ACT* were evaluated at three different T_a values, namely 0°C, 15°C, and 30°C, to represent the typical conditions of winter, shoulder, and summer seasons. These conditions were used to analyze the influence of T_a, *G*, *RH*, and *ACT* on the *CDP*, *CP*, and *WDP* defined by Eq. (11).

Table 5. Case setup for analyzing the influencing factors.

Analyzed parameter	T_a (°C)	G (W/m^2)	RH (%)	ACT (W)
T_a	−10 to 35	326	50	112 (1.87 met)
G	0 (Winter)	0–800	50	112 (1.87 met)
	15 (Shoulder)			
	30 (Summer)			
RH	0 (Winter)	326	10–90	112 (1.87 met)
	15 (Shoulder)			
	30 (Summer)			
ACT	0 (Winter)	326	50	60–240 (1–4 met)
	15 (Shoulder)			
	30 (Summer)			

Figure 9 shows the influence of outdoor air temperature (T_a) on the *CDP*, *CP*, and *WDP*. From -10 to 30 °C, the *CP* was always higher than 69%. It means that, in this temperature range, over 69% of the target people would feel thermally comfortable in the particular outdoor thermal environment. The maximum probability of *CP* was 90%, occurring when the outdoor air temperature was 12 °C. The results also show that, when the outdoor air temperature exceeded 30 °C, the *CP* significantly dropped to lower than 12% and the *WDP* reached over 88%. It means that, over 88% of the target people would feel "warm" or "hot" when T_a > 30 °C. In general, the outdoor air temperature has a significant impact on outdoor thermal comfort.

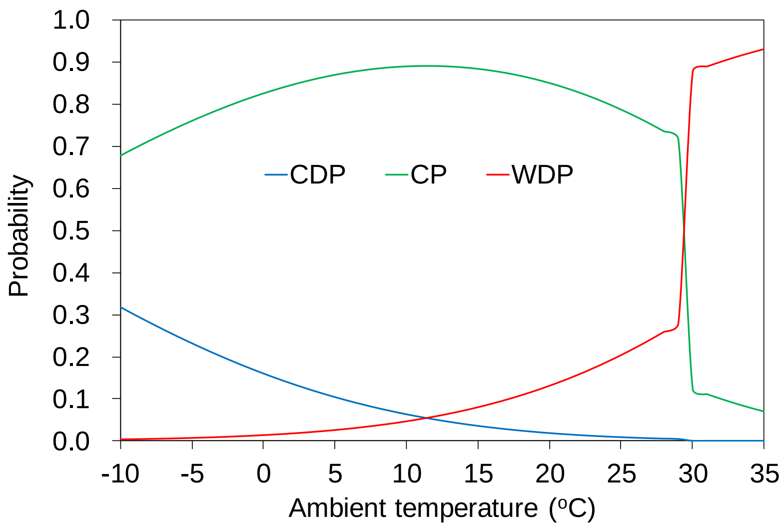


Figure 9. The influence of outdoor air temperature (T_a) on cool discomfort probability (*CDP*), comfort probability (*CP*), and warm discomfort probability (*WDP*).

Figure 10 shows the influence of global radiation on *CDP*, *CP*, and *WDP* at three different outdoor air temperatures, 0 °C, 15 °C, and 30 °C. At 0 °C, increasing the global radiation from 0 to 800 W/m^2 increased the *CP* from 79% to 86%. When the outdoor air temperature was 30 °C, increasing the global radiation led to a 12% decrease in *CP*, from 74% to 62%. The change in *CP* with global radiation was negligible at 15 °C. This was because the increase in the probability of feeling warm or hot was offset by the decrease in the probability of feeling cool or cold. The results indicate that the influence of global radiation on outdoor thermal comfort depends on the outdoor air temperature.

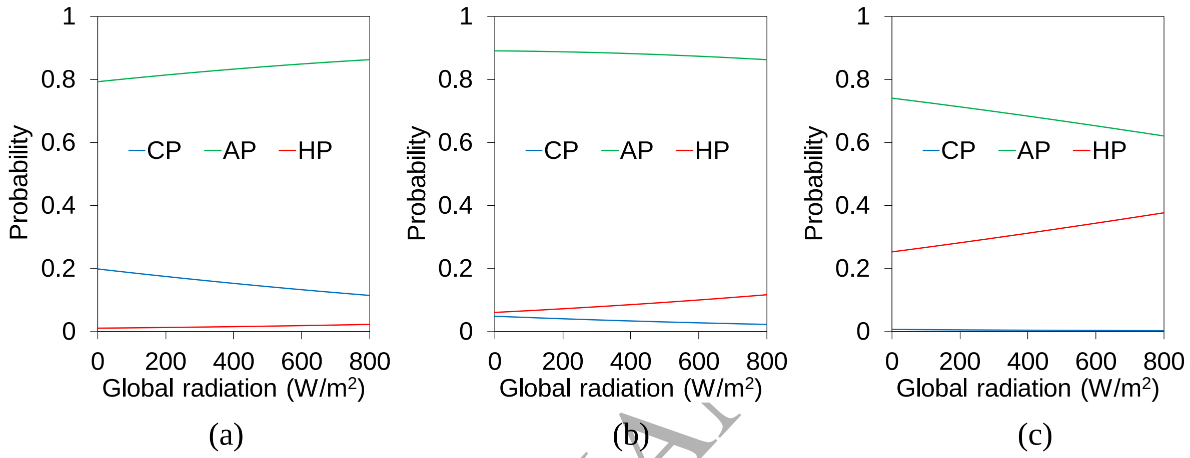


Figure 10. The influence of global radiation on cool discomfort probability (*CDP*), comfort probability (*CP*), and warm discomfort probability (*WDP*) at outdoor air temperatures of (a) 0 °C, (b) 15 °C, and (c) 30 °C.

Figure 11 shows the influence of relative humidity, from 10% to 90%, on *CDP*, *CP*, and *WDP* at three different outdoor air temperatures, 0 °C, 15 °C, and 30 °C. The results show that the relative humidity has minimal influence on *CP* when the outdoor air temperature is 0 °C or 15 °C. However, at 30 °C, increasing the relative humidity from 10% to 90% decreased *CP* by 12%. This is because the air's capacity to hold water vapor increases with temperature [50]. When the relative humidity increased from 10% to 90%, the water vapor pressure P_w increased by 3.40 kPa at 30 °C, which led to the significant influence shown in Figure 11(c). However, the increases in P_w were only 0.49 kPa and 1.36 kPa, respectively, when the outdoor air temperature was 0 °C and 15 °C, so that the influence was minimal, as shown in Figure 11(a) and (b).

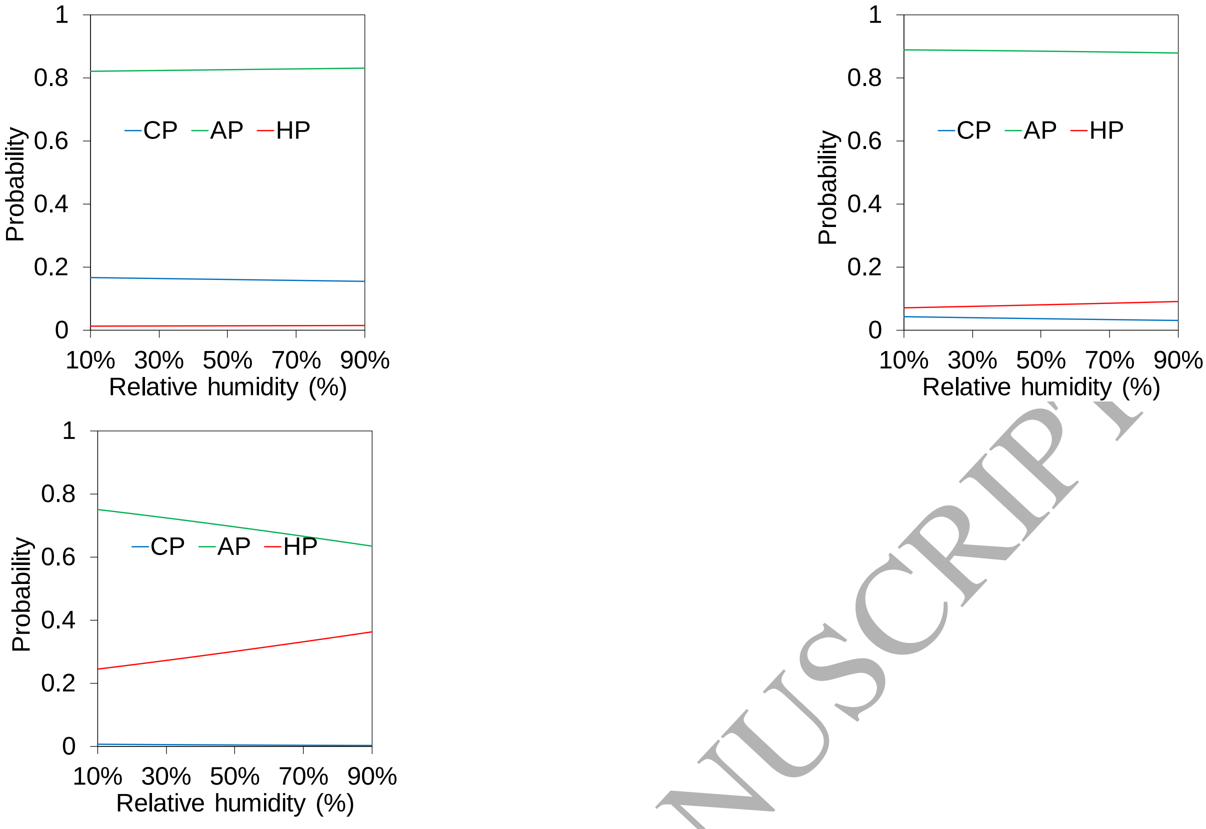
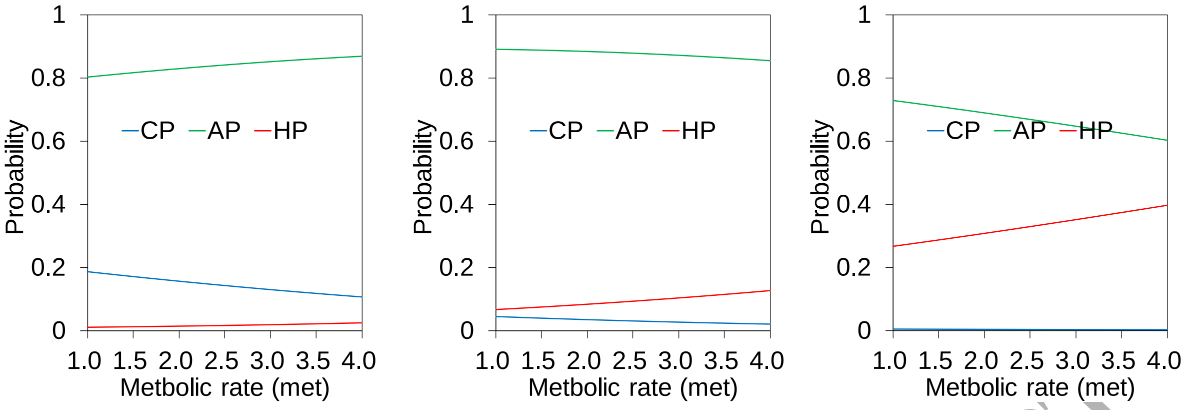


Figure 11. The influence of relative humidity on cool discomfort probability (*CDP*), comfort probability (*CP*), and warm discomfort probability (*WDP*) at outdoor air temperatures of (a) 0 °C, (b) 15 °C, and (c) 30 °C.

Figure 12 shows the influence of activity level on *CDP*, *CP*, and *WDP* at 0 °C, 15 °C, and 30 °C. The increase in activity level increased *CP* from 80% to 87% at 0 °C, but decreased the *CP* from 73% to 60% at 30 °C. The extra heat generation due to a higher activity level in a cold environment helps an individual to maintain thermal comfort to some extent. Therefore, increasing activity level at low temperatures is desirable. However, in a hot environment, reducing heat generation due to activities helps to maintain thermal comfort. At 15 °C, the influence of activity level on outdoor thermal comfort was less significant.



(a) (b) (c)

Figure 12. The influence of activity level on cool discomfort probability (*CDP*), comfort probability (*CP*), and warm discomfort probability (*WDP*) at outdoor temperatures of (a) 0 °C, (b) 15 °C, and (c) 30 °C.

In summary, the outdoor air temperature was the most influential factor on outdoor thermal comfort. A change in outdoor air temperature from −10 to 35 °C led to a difference of nearly 80% in *CP*. However, for the other factors, the influence was much weaker. Among global radiation, relative humidity, and activity level, the maximum change in *CP* was 13%, caused by the activity level changing from 1 to 4 met. In addition, the influence of these factors on *CP* was related to outdoor air temperature. Increasing global radiation and activity level both increased *CP* at a low outdoor air temperature. However, they resulted in a lower *CP* at a high outdoor air temperature. The influence of relative humidity was significant when the outdoor air temperature was high, i.e., 30 °C. These findings can be used for the qualitative assessment of outdoor thermal comfort.

There was a limitation for the analysis above. The objective of the analysis was to examine the sensitivity of each influencing parameter on the predicted thermal comfort. Therefore, when looking at the sensitivity of one parameter, the other parameters were assumed as constants. However, the meteorological variables, such as T_a, *RH*, and *G*, actually depend on each other. Thus, the scenarios analyzed above may not be realistic. To consider the inter-correlation of the meteorological variables, the following section will show a case study for a more realistic scenario, which used the actual meteorological data for Tianjin in 2016.

3.4 Application of the ordered probability model

This section shows how the ordered probability model can be applied to predict suitable times for holding outdoor activities in Tianjin, to provide a guideline for outdoor space design or outdoor activity planning. When planning an outdoor activity, the organizers will want to attract as many people as possible for commercial or other purposes. Outdoor thermal comfort is one of the factors that need to be considered to achieve this aim. Planners need to know how many people will feel thermally comfortable at a given outdoor temperature, so that they can avoid dates and times with undesirable weather.

This study assumed that hours during which the comfort probability (*CP*) is over 80% and outdoor air pollution is lower than China's national standard are suitable for holding outdoor activities. Note that planners can set the threshold for *CP* at any value; 80% was chosen here because it is widely used in ASHRAE [51] and ISO [52] standards and in many thermal comfort studies [46-49]. We used the hourly outdoor meteorological parameters for Tianjin in 2016, including T_a, *RH*, and *G*, from a database website (www.wunderground.com) to calculate the year-round hourly suitability of holding an outdoor activity. Hourly air quality index (AQI) data obtained from the China National Environmental Monitoring Station, Environmental Monitoring of China (http://datacenter.mep.gov.cn/) were used to check if outdoor air pollution was unacceptable. The data from the nearest monitoring station was used. For a given hour, the *CP* was calculated using the developed ordered probability model, i.e. Eq. (7), with these inputs. If the calculated *CP* was greater than 80% and the AQI was lower than the standard, this hour was considered to be suitable for holding outdoor activities.

Figure 13 shows the year-round suitable time periods for holding outdoor activities in Tianjin in 2016 estimated using the ordered probability model. The hours labeled in gray are those when outdoor air pollution was severe, with an AQI above the national standard of 150. The results show that 19.2% of the year was highly polluted and not suitable for holding outdoor activities. The majority of these highly polluted time periods occurred in winter. It was also found that 32.6% out of the 5840 hours (from 6 a.m. to 21 p.m.) were thermally acceptable and not polluted, as labeled in green. These time periods were considered to be suitable for holding outdoor activities. They mainly occurred during the shoulder seasons, indicating that April and October are the most suitable months for holding outdoor activities. In early and late winter (March and November), the suitable hours were mostly in the afternoon, while the suitable hours in early and late summer were mostly in the morning and dusk periods. The hot and cold time periods are labeled in red and blue, respectively. Based on the results, the total hot period (31.4%) was longer than the total cold period (16.8%). As a result, when designing outdoor spaces or planning outdoor activities in Tianjin, most attention should be paid to how to reduce heat stress in summer.

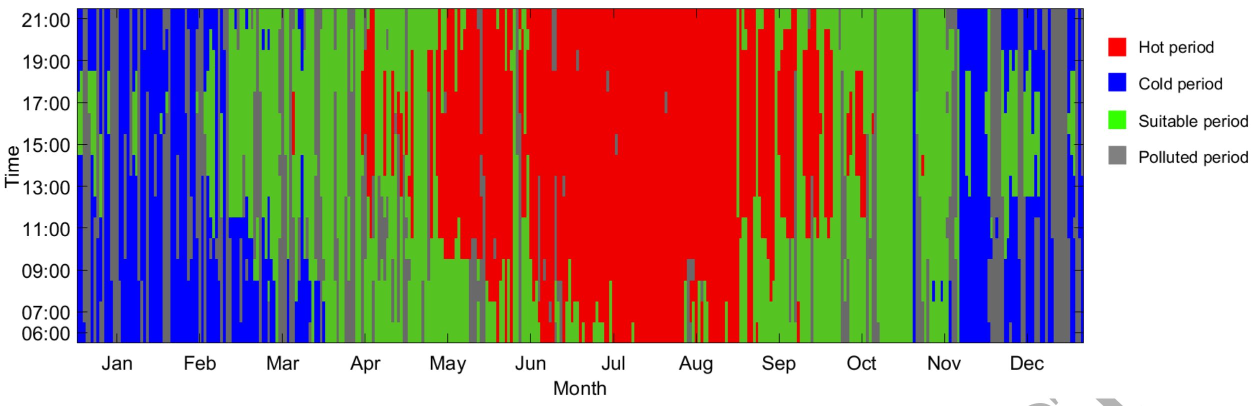


Figure 13. Year-round suitable time periods for holding outdoor activities in Tianjin predicted by the developed ordered probability model.

4. Discussion

There are a number of limitations to consider for this study, beginning with the statistical nature of the ordered probability model, which is not based on physical or physiological principles and is thus limited to the climate regions from which the data are obtained. To improve its predictive capability, more data should be used to train the model. Furthermore, the ordered probability model is just one kind of probability-based model. Other probability-based models include the multinomial logit model [53] and categorical neural network model [54]. This paper provides an idea of how a probability-based model may provide additional information over traditional single-value models. Comparisons between different probability-based models should be made in the future. Although the aim of this study was to develop an ordered probability model for outdoor thermal comfort, a model for indoor thermal comfort could also be developed by using the same method and indoor data. More work is needed on the development and application of probability-based models to improve predictions of thermal comfort.

Furthermore, the TSV dataset used in this study was based on a discrete scale. However, using a continuous scale could be a better strategy for obtaining a higher R^2. From the perspective of methodology, the proposed ordered probability model can also be applied for continuous TSV datasets. First, we can convert them to discrete TSVs with small intervals (e.g. [-3, -2.9), …, [-0.1, 0), [0, 0.1), …, [2.9, 3]). Then, an ordered probability model with more vote options can be developed using the same method shown in this study. To further improve the accuracy of the predictive model, it would be worthwhile to use a continuous TSV dataset, if available, to develop an improved ordered probability model for predicting outdoor thermal comfort in the future. In addition, it would be great to have a new set of survey data to validate the developed models. Unfortunately, such a new dataset from the similar climate region is currently unavailable. Therefore, it would also be worthwhile to conduct an independent outdoor thermal comfort survey in Tianjin in the future to further validate the developed models.

5. Conclusions

This study developed an ordered probability model for predicting the probability distribution of outdoor thermal comfort by using 1549 observations obtained from a field survey in Tianjin. The predictive capability of the ordered probability model was systematically assessed by comparing it with the survey data and a traditional multivariate linear model. A sensitivity analysis of the ordered probability model was conducted to investigate the influence of various factors on comfort probability. Furthermore, the developed model was applied to predict the year-round suitable time periods for holding outdoor activities in Tianjin. The following conclusion can be drawn:

1. The ordered probability model has similar accuracy to the multivariate linear model in terms of predicting single-value TSVs.
2. The ordered probability model can provide a more realistic prediction of the probability distribution of TSVs than the multivariate linear model.
3. Outdoor air temperature has the most influence on outdoor thermal comfort. The influence of other parameters, including global radiation, relative humidity, and activity level on predicted thermal sensation depend on the outdoor air temperature.
4. The developed model predicts that 32.6% of the year is suitable for holding outdoor activities in Tianjin.

Acknowledgement

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Graphic abstract