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An Artificial Neural Network-based model that can predict inpatients' personal thermal sensation in rehabilitation wards

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ABSTRACT

Indoor thermal comfort is important to hospital designs as it affects healthcare outcomes. However, existing thermal sensation analysis models do not fully consider individual patient's preference and their effectiveness has not been validated in healthcare environments. The commonly used Predicted Mean Vote (PMV) model cannot process complex parameters such as individual differences, multiple patients' biosignals, medical activities, and spatial layout of wards, etc. To fill in the gaps, this research aims to develop an innovative model that can effectively predict inpatients' personal thermal sensation in rehabilitation wards. Based on previous research on machine learning (ML), a prototype of the Artificial Neural Network (ANN)-based model has been developed for this purpose. To test this model and assess its prediction accuracy in the real world, a case study was conducted in the rehabilitation department of a general hospital in Xuzhou, China. The results indicated that the ANN-based model effectively predicted patients' thermal sensation. Moreover, it was found from this study that the incorporation of spatial and health-related parameters into the ANN-based model could significantly improve the prediction accuracy. The best prediction accuracy of the ANN-based model was 8.10 % higher than that of the baseline model. It is therefore concluded that this model can be used to support architects and HVAC system engineers to make informed decisions in hospital designs and help medical staff allocate in-patients according to their preference.

1. Introduction

A good indoor thermal environment can significantly enhance the health, well-being, and productivity of occupants [1,2]. The indoor thermal environment is important in hospital designs as keeping inpatient rooms in a good thermal comfort level can help patients, who are often more vulnerable and sensitive to their surroundings than healthy individuals [3], maintain positive emotions and thereby promote their healing outcomes [4]. Previous research in this field focused on occupants' average thermal comfort level by considering air temperature, relative humidity, air velocity, mean radiant temperature, clothing insulation, and metabolic rate [5].

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Other research revealed that individuals might have different perceptions of indoor temperatures under identical environmental conditions (Zhe et al., 2018), which indicated that ‘individual differences’ should be taken into account for a more personalized design of the indoor thermal environment. In addition, some researchers found that the spatial design (including building orientation, indoor spatial layout, and occupants’ indoor locations, amongst other parameters) could influence building occupants’ thermal comfort (Du et al., 2013). Moreover, patients’ perceived thermal comfort in rehabilitation wards might also be influenced by their health conditions and the healthcare environment [6], as the disease can affect people’s thermal physiology, thermal sensation, metabolism, blood flow, and regulatory responses [7].

To predict thermal sensation, analysis models have been developed over years to predict human thermal comfort. The Predicted Mean Vote (PMV) model has been widely used to investigate indoor thermal comfort in office buildings, educational institutions, and medical environments [5]. However, the PMV model has its limitations [8] as it does not consider individual differences [9,10], spatial parameters, or healthcare parameters. As a result, it has been found unsatisfactory in previous research when using PMV model to predict patients’ thermal comfort [11]. To cope with this issue, some researchers have developed more advanced predictive personal thermal comfort models based on machine learning (ML). For instance, the ML-based model developed by Gong et al. [12] took into account the impact of different spatial parameters on the accuracy of prediction. On the other hand, the existing personal thermal comfort prediction models, which were mainly developed based on healthy subjects, considered only age, gender, and body mass index (BMI). However, these models have not been validated in a medical setting [6], and individual differences have not been properly addressed in these models.

This paper aims to explore the impact of environmental parameters in rehabilitation wards on patients’ personal thermal sensation and to develop a machine learning-based prediction model that can be used to inform future healthcare environment designs.

2. Literature review

2.1. Impact factors of thermal sensation

The parameters included in Fanger’s thermal comfort model (1970), including metabolism, clothing, indoor air temperature, indoor mean radiant temperature, indoor air velocity, and indoor air humidity, are usually recognized as essential factors in thermal sensation research. Additionally, differences in gender, age, and BMI often lead to variations in individuals’ thermal sensation [9,10]. For example, previous research indicated that age and gender had a distinct influence on occupants’ thermal preferences [13]. Another study discovered that variations in body mass and height stimulated differences in skin temperature, leading to changes in an individual’s preferred thermal comfort [14]. Additionally, peoples’ biosignals were proven to influence their thermal sensation. For example, studies demonstrated a strong bond between heart rate and metabolic rate, which influenced building occupants’ perception of heat [15,16]. The correlation between indoor temperature and blood pressure was nonlinear [17], whereas the latter was linearly correlated with human metabolism and activity level [18]. Some studies found that, in response to a thermally uncomfortable environment, peripheral vascular dilatation and perspiration would increase as a means of regulating the body’s temperature and maintaining thermal comfort [19]. Thus, human body temperature, heart rate, and blood pressure will influence a person’s thermal perception. Furthermore, indoor spatial layout [20], the location of an air conditioning system [21] and room orientation [22] can create an uneven indoor heat distribution. This can affect occupants’ thermal perception, depending upon their exact locations in a room. Outdoor weather also has a psychological or direct physical effect on indoor thermal comfort [23]. In addition, some studies claimed that medical treatment, such as massage, acupuncture and intravenous drips, also affected patients’ thermal sensation [24–27].

To summarize, the impact factors of thermal comfort considered in this research include individual differences (i.e., age, gender, and BMI), indoor air temperature and humidity, air speed, mean radiant temperature, occupants’ metabolic rate and clothing insulation, as well as spatial parameters and healthcare-related parameters.

2.2. Thermal comfort investigation in the healthcare environment

At present, the PMV model is the most widely used indoor thermal comfort assessment model around the world (Pereira et al., 2020). It represents the average thermal sensation of all occupants exposed to an identical environment [28]. Fanger proposed his model in 1970 and it was first used in a hospital in 1977 [29]. Since then, the PMV model has been extensively applied to investigate thermal comfort levels in healthcare settings. In addition, the PMV model is widely used in the development of HVAC systems to optimize the overall building performance by reducing energy consumption and improving occupants’ thermal comfort [30–32]. Nevertheless, many researchers have discovered the inconsistencies between the PMV results and the actual thermal sensation [11]. For instance, in an Italian health centre, researchers compared the results of PMV voting and thermal sensation voting (TSV) and found that PMV underestimated the patients’ actual thermal sensation [33]. This is because the PMV was created by primarily using healthy adults as research subjects, without taking into account patients’ unique physiological needs [34]. A study in obstetric wards revealed that the TSV value of pregnant women was +0.97 (warm), while the PMV value was −0.85 (slightly cool) [33]. Furthermore, some parameters that are important in healthcare settings have not been properly considered in the PMV models. For instance, some studies evaluated patients’ thermal comfort in hospitals against their age and gender [35], but not consider the joint effect of biosignals such as heart rate, blood pressure and body temperature. Even when patients’ health status was taken into account, such information was extracted based on patients’ self-description of “very good, good, fair bad, and very bad” rather than their objective biosignal index or specific medical treatment [36]. In addition, there was no research on the effect of indoor spatial layout on patients’ thermal sensation. Therefore, more research needs to be conducted to identify and investigate the factors that influence patients’ thermal comfort.

2.3. Machine learning-based thermal sensation prediction model

A growing number of researchers have proposed data-driven models to predict personal thermal sensation in order to achieve more accurate prediction results than the PMV model [37]. Machine learning (ML) has received considerable attention in these models [11] due to its strong self-study ability, a high-speed computing ability, and a complex problem-solving ability [38,39]. ML has demonstrated its superiority in predicting personal thermal comfort in academic buildings, offices, and residential environments. Some scholars asserted that, on average, the prediction result of ML-based thermal sensation prediction model was 40 % more accurate than that of the PMV model ([40] [41]). An investigation by Gong et al. [12] found that the average prediction accuracy of the PMV model was 27.63 % whereas the ML-based model was 70.93 %. In addition, ML is more adept than PMV at handling non-standard and nonlinear relationships [39]. For example, Katić et al. [14] compared the effectiveness of Support Vector Machines (SVM) with four different Kernel functions (Linear, Quadratic, Cubic and Gaussian) and Ensemble Algorithms (Boosted trees, Bagged trees and RUS-Boosted trees) on a personal model in an office building by considering occupants' gender, weight, and age. The results showed that all these ML algorithms could effectively predict personal thermal comfort levels, and the optimal algorithm achieved a mean accuracy of 84 % using RUSBoosted trees. A research team proposed a deep neural network-based multi-task learning model to predict occupants' thermal comfort in schools, and the model achieved a maximum accuracy of nearly 90 % [42]. Another study [43] employed several machine learning algorithms, including SVM, Decision Tree, K-Nearest Neighbors (KNN), Discriminant Analysis, and ensemble methods, to establish individual thermal comfort prediction models in a controlled climate chamber. The prediction models incorporated various personal features and assigned significant importance to skin temperature performance during model development. Among these models, the KNN-based approach demonstrated the best prediction accuracy, achieving 83.6 %. Lu et al. [44] established individual thermal models with consideration of skin temperature at an academic institution using Random Forest (RF) and SVM. The final result demonstrated that the linear kernel SVM-based model had the highest degree of accuracy, exceeding 97 %. Multiple studies have demonstrated that an artificial neural network (ANN) excels at predicting thermal sensation vote outcomes [38]. Shan et al. [45] proposed an ANN-based personal thermal sensation prediction model which achieved an average prediction accuracy of 89.2 %. Gong et al. [12] included spatial impact in an ANN-based prediction model and the prediction results were better than KNN and SVM by up to 12.6 %. However, all these prediction models have not been validated in healthcare settings. The existing ML-based prediction model has also not taken into account healthcare-related parameters such as biosignals and medical treatment. Furthermore, the impact of spatial design on the ML-based prediction models has not been explored in healthcare environments. Since spatial parameters and healthcare-related parameters of patients have a significant impact on their thermal sensation, these parameters need be taken into consideration when predicting patients' personal thermal sensation.

3. Proposed methodology

A methodology has been devised to integrate spatial parameters and patients' healthcare-related parameters into the personal thermal sensation prediction model (Fig. 1).

The methodology has four phases, which are: (i) identifying parameters for model development; (ii) fieldwork; (iii) developing the model; and (iv) results analysis. In the first phase, the parameters were categorised into personal-dependent parameters,

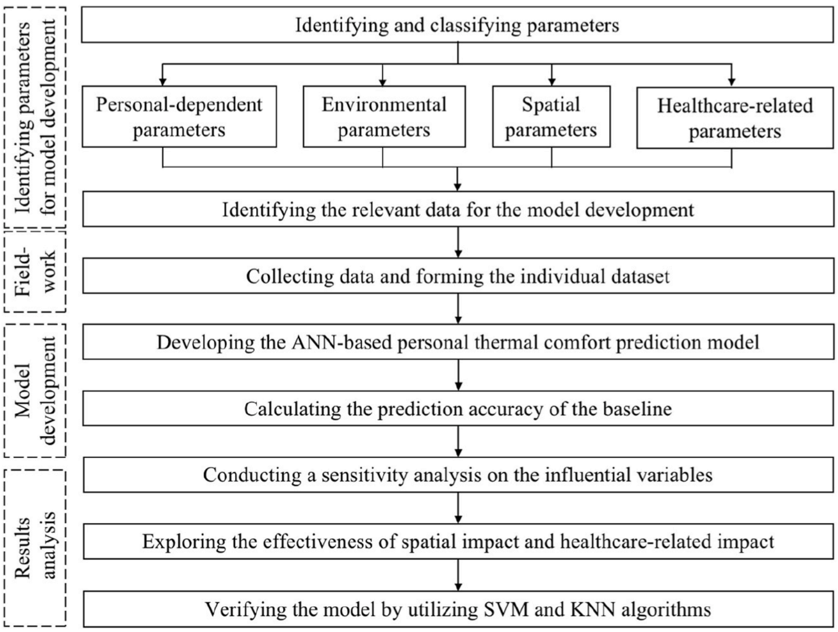

Fig. 1. The proposed methodology.

environmental parameters (including both indoor and outdoor environmental parameters), spatial parameters and healthcare-related parameters, as shown in Table 1. The data used for developing this model were identified based on real-world conditions. Fieldwork was then conducted in the subsequent phase to collect the relevant data. In the model development phase, the individual datasets were formed and used to develop an ANN-based personal thermal sensation prediction model. The following results analysis phase examined the impact of various influential parameters on prediction accuracy. The ANN-based models that covered all parameters (including spatial parameters and healthcare-related parameters) have been evaluated against a baseline model which only uses conventional parameters such as personal-dependent parameters and environmental parameters. This allows the relative importance of single and combined influential variables concerning the prediction accuracy to be ranked based on a sensitivity analysis. Lastly, the SVM and KNN machine learning (ML) algorithms have been employed to validate the results of the ANN-based model.

3.1. Identifying parameters for model development

This study considered the essential parameters in PMV, such as the clothing insulation level and metabolic rate of the subjects, as well as the environmental parameters of average indoor air temperature, relative humidity, airspeed and mean radiant temperature. Meanwhile, individual differences, including age, gender and BMI, were also considered in the personal prediction model. The aforementioned parameters were categorised into personal-dependent and indoor environmental parameters.

The ANN-based personal thermal sensation prediction model was developed by incorporating spatial and healthcare-related parameters. The spatial parameters consisted of the surface temperature and three-dimensional coordinates of the windows, doors and air conditioning outlets, which were calculated using Equation (1). The ambient environment of the subjects and the orientation of the windows were also recorded. The healthcare-related parameters included personal biosignals (including body temperature, heart rate and blood pressure) and the form of medical treatment (including acupuncture, physical therapy, massage and intravenous drip). Finally, the impact of the outdoor environment was considered, including the outdoor temperature, relative humidity and weather (including sunny, cloudy, overcast, and rainy).

$$(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) = (|x_1 - x_2|, |y_1 - y_2|, |z_1 - z_2|) \tag{Eq.1}$$

where, x_1 and y_1 are the coordinates of the subject's location in the x- and y-axes; z_1 is the height of the subject's forehead; x_2, y_2 and z_2 are the coordinates of the centre points of the windows, doors and air conditioner outlets on the x-, y- and z-axes, respectively.

3.2. Detailed setting of the ANN model

Fig. 2 depicts the general structure of the four-layer ANNs used in this study. The end-to-end ANN structure included an input layer, two hidden layers, and a classification output layer, with the number of nodes corresponding to the number of input features (i.e. forty) and thermal comfort scale (i.e. 7), respectively. The size of the employed ANN (i.e. number of hidden layers and number of nodes per layer) was determined by balancing prediction accuracy and processing time. Specifically, it was found that, using ANNs of the current size, the prediction accuracy was close to saturation. Increasing the size of ANNs marginally improved prediction accuracy but substantially increased the processing time. In addition, the linear rectification function (ReLU) was utilized as the activation function,

Table 1
Parameters' identification and classification.

Categories	Features	Description	
Personal-dependent parameters	Subject's basic information	Age, gender and BMI	
	Metabolic rate	Obtained by using ASHRAE-2010	Met Units
	Clothing insulation level		clo
	Bedding insulation level	No cover (0.9 clo), blanket (1.65 clo), thin quilt (1.98 clo), thick quilt (2.7 clo), thick quilt more than 1 layer (3.38 clo) [46]	clo
Indoor environmental parameters	Indoor environment	Average indoor air temperature, humidity and air speed	Temperature (°C); Humidity (%); Air speed (m/s)
	Mean Radiant Temperature	Calculated by using ASHRAE-2010	°C
Outdoor environmental parameters	Outdoor weather	Outdoor temperature, humidity and weather condition	Weather condition: sunny (1), cloudy (2), overcast (3), and rainy (4)
Spatial parameters	Surface temperature of windows, doors and heat sources	Heat sources including windows, air outlets of air conditions, and door	°C
	Tree-Dimensional Cartesian coordinates	The distances of subjects to windows, doors and heat sources in three dimensions	(X-axis, Y-axis, Z-axis), which were calculated by using Equation (1).
	Orientation (O)	The window face north, or south	Northward, and southward were recorded as (N) and (S)
	Ambient environment (AE)	The air temperature and humidity	Temperature (°C); Humidity (%)
Healthcare-related parameters	Personal biosignal	Daily health monitoring report, which contains body temperature, heart rate blood pressure (both systolic and diastolic).	Body temperature (°C) Heart rate (times/minute) Blood pressure (mmHg)
	Medical treatment	The instantaneous medical treatment which was conducted at the data collection slots	No treatment, acupuncture, physical therapy, massage, and infusion were recorded as (0), (1), (2), (3) and (4) respectively.

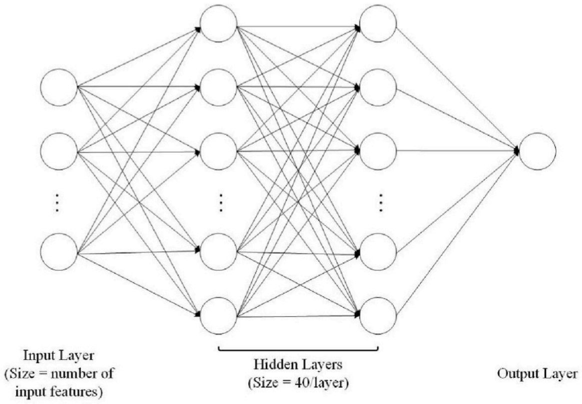

Fig. 2. The end-to-end artificial neural network structure ([12], adapted).

while the cross-entropy was utilized as the loss function. The dataset was randomly divided into a training set (70 %) and a test set (30 %) for each training session of the ANN, and the ANN was optimized using the scaled conjugate gradient method. To minimize the impact of the randomness associated with weight initialization and dataset partitioning, the performance of each feature combination was measured as the average test accuracy of one thousand training sessions.

3.3. Exploring the effectiveness of influential parameters

An ablation experiment was conducted to investigate the impact of spatial parameters on prediction accuracy. The sensitivity coefficient (SC) was calculated by the increasing rate based on the baseline model, as shown in Equation (2) [47], for evaluating the contribution.

$$\boldsymbol{SC} = (\boldsymbol{A_1} - \boldsymbol{A_0}) \, / \, \boldsymbol{A_0} \tag{Eq.2}$$

In addition, RMSE (Root Mean Squared Error) value was computed to represent the discrepancies between the predicted and actual values. With the same prediction accuracy, the higher the RMSE value, the closer is the predicted value to the real one. It could be used to describe the robustness of the model.

$$\mathbf{RMSE} = \sqrt{\sum_{\mathrm{i=1}}^{\mathbf{n}} \frac{(\widehat{y}_i - y_i)^2}{\mathbf{n}}} \tag{Eq.3}$$

where, A_0 was the predicting accuracy when considering personal-dependent and environmental parameters only; A_1 was the predicting accuracy when considering personal-dependent, environmental, spatial and healthcare-related parameters; y_i was the measured value; $\widehat{y}_i$ was the predicted value; $\overline{y}$ was the mean value.

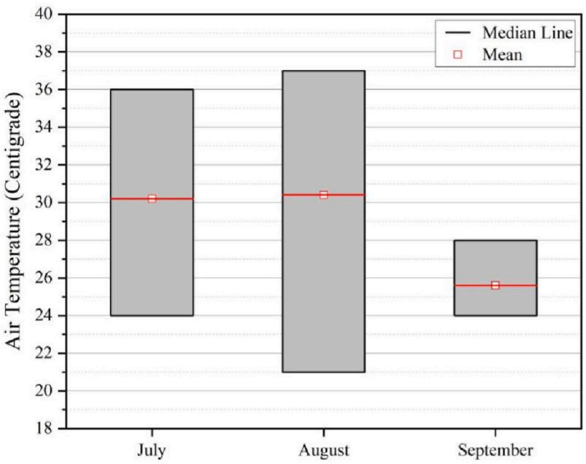

Fig. 3. Outdoor air temperature during the experimental period.

4. Fieldwork

4.1. Study area

Xuzhou is a city located at 33° 43′–34° 58′ N, 116° 22′–118° 40′E in Eastern China and has a middle latitude monsoon climate with four distinct seasons [48]. The city's annual average temperature is 14 °C and its annual average precipitation is about 800–930 mm [49]. Dual air conditioning systems are the primary mechanism used in Xuzhou for heating during the winter and cooling during the summer.

The fieldwork for this study was conducted between the 1st July and the 3rd September 2022, which were typical summer months in this region. As shown in Fig. 3, the outdoor air temperature during the experiment days ranged from 21 °C to 37 °C, with an average of 29.9 °C. There were four weather conditions during the experiment period (Fig. 4): sunny (53.01 % of the time), cloudy (30.12 %), overcast (12.05 %) and rainy (4.82 %). Fig. 5 shows the indoor temperature measured throughout the experiment. In the hospital wards used for research, the average indoor temperature ranged from 20.0 to 27.1 °C.

4.2. Experiment setting

The experiments were conducted in the hospital's rehabilitation department, which was located on the fifth floor of the five-storey medical building. Eleven wards, including four rooms facing north and seven rooms facing south, were used for field experiments. As shown in Figs. 6 and 7, each ward was designed in a standard layout, consisting of three inpatient beds, one bathroom, four windows, one door and one air conditioning unit. The size of the southern rooms is 3.93 m × 9.9 × 2.8 m, with a floor area of 39 m^2, while the northern rooms measure 3.93 m × 9.09 m x 2.8 m and a floor area of 35.7 m^2. In addition, the window-to-wall ratio of all rooms was 0.487.

Six digital thermometers were used to measure the indoor air temperature, all positioned at a height of 1.1 m to comply with ASHRAE standards [50]. However, to prevent any negative impact on activities in the wards, it was not possible to hang the thermometers in the actual hospital wards instead of attaching them directly to the walls as required by ASHRAE standards. To address this issue, 5-mm thick nano-adhesives were used to attach the thermometers to the walls, resulting in a negligible measurement error. According to Kim (2017), the skin on the forehead is the most sensitive to changes in temperature. To measure the ambient air temperature in the study, three additional thermometers were placed next to the patients' pillows, at the same level as their foreheads when lying down. The coordinates of the centre points of the windows, doors, air conditioning units and subject locations were also recorded.

4.3. Subjects' information

During the experiment period, all conscious patients undergoing neurorehabilitation in the rehabilitation ward, aged between 18 and 80 years, were recruited as subjects. Finally, twenty-seven Chinese patients under neurological rehabilitation were participated as subjects, including six females and twenty-one males. Their physiological information is shown in Table 2.

4.4. Fieldwork procedure

Compared to healthy individuals, patients in healthcare environments are generally more sensitive to environmental changes due to their weakened physical and psychological states. This has made it difficult to take the indoor temperature as a variable in healthcare research, although it has been recommended by ASHRAE's standards for a real-world healthcare setting. This research has conducted real-world data collection to obtain environmental data, subjects' information and thermal sensation voting results without any environmental interference. Before conducting this fieldwork, personal information (e.g. age, gender and BMI) and daily health data (e.g. body temperature, heart rate and blood pressure) were extracted from the participants' clinical records. Meanwhile, the

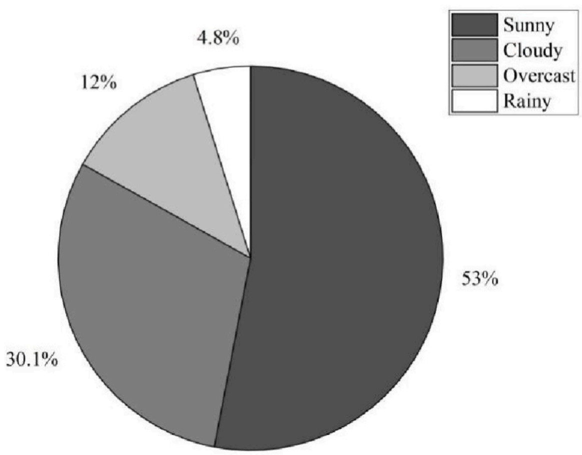

Fig. 4. Outdoor weather condition during the experimental period.

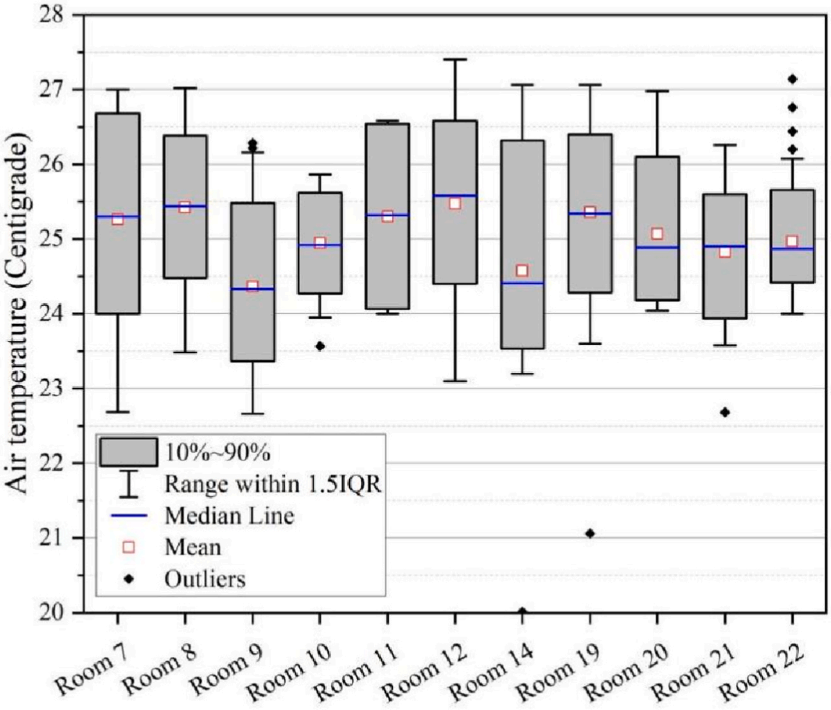

Fig. 5. The average indoor temperature of each experimental wards.

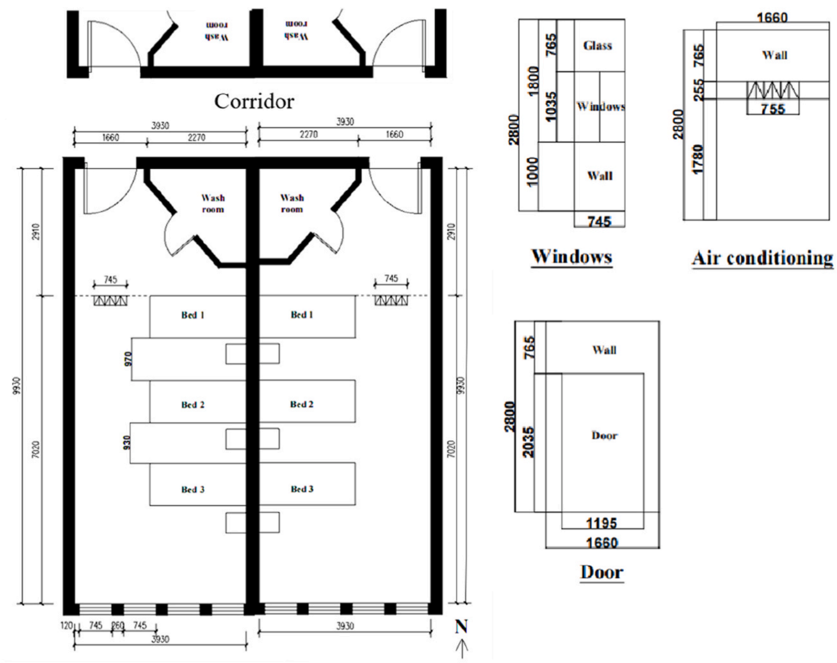

Fig. 6. The layout of the experiment wards.

locations of windows, doors, air conditioning outlets and patient beds were also recorded.

At 9.00 a.m., 12.00 a.m., 2.00 p.m. and 4.00 p.m. of each day, four data collection tasks were conducted. The insulation level of the subjects' clothing and bedding, their metabolic rates, the outdoor temperature, the indoor temperature and relative humidity at different locations, the indoor wind speed and the subjects' ongoing medical treatments were also recorded at each data collection slot. Meanwhile, the results for patients' thermal sensation level were collected on a regular basis using the ASHRAE 7-point thermal

Fig. 7. The rehabilitation ward and monitoring devices.

Table 2
Physiological information of participants.

Subject	Gender	Age (years)	Height (m)	Weight (kg)	BMI	Disease
1	Male	55	1.67	60	21.51	Cerebral haemorrhage
2	Female	75	1.60	65	25.39	Cerebral infarction
3	Male	66	1.85	66	35.06	Cerebral infarction
4	Male	65	1.65	58.5	21.49	Cerebral haemorrhage
5	Male	46	1.77	75	23.94	Cerebral haemorrhage
6	Female	74	1.62	64	24.39	Hemiplegia
7	Male	67	1.65	65	23.88	Cerebral infarction
8	Male	60	1.73	62	20.72	Hemiplegia
9	Male	71	1.70	62.5	21.63	Cerebral infarction
10	Male	70	1.75	62.5	20.41	Hemiplegia
11	Male	85	1.63	60	22.58	Cerebral infarction
12	Male	59	1.72	61	20.62	Carotid-cavernous fistula infarction
13	Female	48	1.58	60	24.03	Cerebral infarction
14	Female	59	1.60	60	23.44	Cerebral infarction
15	Female	74	1.57	60	24.34	Thalamic haemorrhage
16	Male	66	1.65	75	27.55	Extracerebral haemorrhage
17	Male	67	1.65	65	23.88	Cerebral infarction
18	Male	62	1.54	60	25.3	Hemiplegia
19	Male	81	1.70	70	24.22	Cerebral infarction
20	Male	70	1.70	80	27.68	Cerebral haemorrhage
21	Male	64	1.74	75	24.77	Cerebral infarction
22	Male	67	1.60	57	22.27	Cerebral haemorrhage
23	Male	55	1.70	60	20.76	Cerebral haemorrhage
24	Female	66	1.60	65	25.39	Hemiplegia
25	Male	69	1.73	65	21.72	Cerebral infarction
26	Male	80	1.70	65	22.49	Cerebral infarction
27	Male	69	1.70	70	24.22	Cerebral haemorrhage

sensation voting scale [−3 (cold), −2 (cool), −1 (slightly cool), 0 (neutral), 1 (slightly warm), 2 (warm), and 3 (hot)], as depicted in Fig. 8. However, most subjects were patients over 60 years old who had visual impairment and difficulty in reading. Consequently, the authors read the thermal sensation voting question to the participants without giving them any additional instruction or information that could potentially interfere with their choices. The instantaneous air temperature and relative humidity were recorded in each data collection slot. Xiaomi Bluetooth thermometers were used to measure the indoor air temperature and relative humidity (RH) with an accuracy within 0.1 °C and 1 % RH over a measuring range of 0°C-60 °C for temperature and 0%–99 % for RH, respectively. The surface temperature of the windows, doors and air conditioners was measured using a FLIR E85 thermal camera with a −20 °C–120 °C measuring range and an accuracy of within 2 °C. In addition, Testo 405i anemometers were used to measure air velocity with a

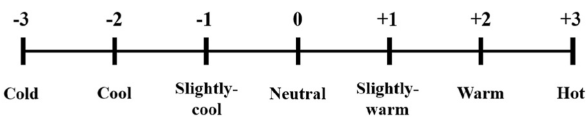

Fig. 8. ASHRAE 7-scale Thermal Sensation scale [51].

measuring range of 0–10 m/s and an accuracy of 0.1 m/s.

4.5. Academic ethics consideration

The field experiment has been approved by the university's research ethics committee (19-02-79). Before the beginning of the experiment, the subjects were fully informed of the objective and content of the experiment. The attending physician of the subjects oversaw the data collection process.

5. Results and analysis

In total, 1304 individual thermal sensation voting responses were collected and a baseline of model prediction accuracy was then calculated. The spatial variables included windows (marked as W1, W2, W3 and W4 from west to east), door (D), air conditioning unit (AC), ambient environment (AE) and room orientation (O). The individual healthcare-related parameters included body temperature (BT), heart rate (HR), blood pressure (BP) and medical treatment (MT). As a result, in total, there were 32,767 combinations of these variables. The prediction accuracy of the model with these combinations could then be calculated and compared with the baseline model. This allowed for the top ten combinations within the spatial category, healthcare-related category and both categories to be identified, which will be discussed in detail in the following sections. These combinations could also be used to inform the discussion on the impact of outdoor weather on model accuracy. The top one hundred combinations among all the variables were explored to identify the parameters with had the most significant impact on the accuracy of the prediction model.

5.1. The influence of spatial variables

5.1.1. The influence of single spatial variables

As shown in Table 3 and Fig. 9, when a single spatial variable is considered, there is an improvement in the accuracy of prediction model, except for W1 and W2. When considering all windows, the maximum accuracy reached 0.733, which is 2.21 % higher than the baseline model. Moreover, the model that considered all windows has a lower RMSE value (0.5597) than the baseline model (0.5937). This was followed by the integrated considerations of W1+W2+W3 and W1+W4, which led to accuracies of 0.7322 and 0.7318 with 2.09 % and 2.03 % improvements, respectively. The impact of multiple windows on the accuracy of the prediction model was also more significant than that of a single window – the average single-window prediction accuracy was 0.7152, while multiple-window prediction accuracy was 0.7281. The model with multiple windows performed better in RSME (with a mean value of 0.5688) than the one with a single window (with a mean value of 0.5842).

AC and O also had substantial impacts on improving prediction accuracy, with respective accuracies of 0.7286 (with an increase of 1.59 %) and 0.7272 (with an increase of 1.49 %). D, meanwhile, improved prediction accuracy by 0.76 %. The models considering D, AC and O had lower RSME values (0.5642, 0.5642 and 0.5733, respectively). However, the effect of AE was smaller than that of other spatial variables, increasing by 0.28 % compared to the baseline model, while AE did not affect the robustness of the model.

5.1.2. Top ten combinations of spatial variables

In addition to the single spatial element combinations discussed previously, a total of 255 combinations were analyzed that considered multiple spatial elements. Among these, the top ten combinations with the highest prediction accuracy have been presented in Table 4 and Fig. 10. The optimal combination, which considered W1, W2, W4, AC, AE and O, increased accuracy by 7.36 % compared to the baseline model, reaching an accuracy of 0.77. Moreover, it had a lower RMSE value of 0.5157.

The results of the analysis demonstrated that combinations of multiple spatial factors exhibited higher prediction accuracy than

Table 3
The results of personal thermal sensation predication model considering single spatial variables.

Variable	Accuracy	SC value	RMSE
Baseline model	0.7172	0.00 %	0.5937
Window 1 (W1)	0.7008	−2.28 %	0.5905
Window 2 (W2)	0.7127	−0.63 %	0.5841
Window 3 (W3)	0.7245	1.02 %	0.5843
Window 4 (W4)	0.7228	0.78 %	0.5190
Window 1 +Window 2 (W1+W2)	0.7276	1.46 %	0.5889
Window 1 +Window 3 (W1+W3)	0.7288	1.62 %	0.5818
Window 1 +Window 4 (W1+W4)	0.7318	2.03 %	0.5282
Window 2 +Window 3 (W2+W3)	0.7265	1.30 %	0.5672
Window 2 +Window 4 (W2+W4)	0.7243	0.99 %	0.5533
Window 3 +Window 4 (W3+W4)	0.7264	1.29 %	0.5703
Window 1 +Window 2 +Window 3 (W1+W2+W3)	0.7322	2.09 %	0.5795
Window 1 +Window 2 +Window 4 (W1+W2+W4)	0.7271	1.38 %	0.5795
Window 1 +Window 3 +Window 4 (W1+W3+W4)	0.7477	3.01 %	0.5544
Window 2 +Window 3 +Window 4 (W2+W3+W4)	0.7235	0.88 %	0.5416
Window 1 +Window 2 +Window 3 +Window 4 (W1+W2+W3+W4)	0.7330	2.21 %	0.5597
Door (D)	0.7226	0.76 %	0.5642
Air conditioning (AC)	0.7286	1.59 %	0.5642
Ambient environment (AE)	0.7192	0.28 %	0.5829
Orientation (O)	0.7273	1.41 %	0.5733

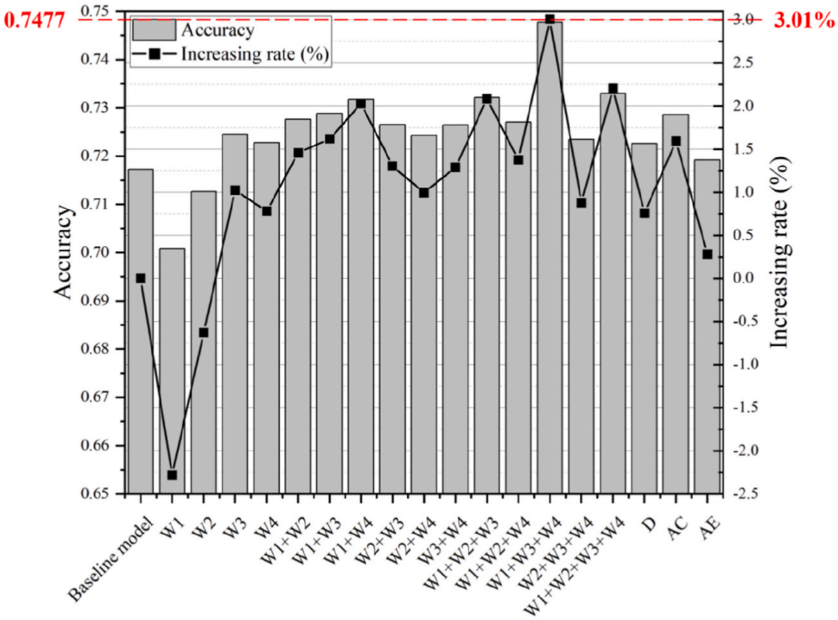

Fig. 9. The results of personal thermal sensation predication model considering single spatial variables.

Table 4
The results of models among all spatial variables with Top 10 accuracy.

Combination	Accuracy	SC value	RMSE
Baseline model	0.7172	0.00 %	0.5937
Window 1+ Window 2+ Window 4+ Air conditioning + Ambient environment + Orientation (W1+W2+W4+AC + AE + O)	0.7700	7.36 %	0.5157
Window 4+ Door + Ambient environment + Orientation (W4+D + AE + O)	0.7680	7.08 %	0.5257
Window 1+ Window 3+ Window 4+ Door + Ambient environment + Orientation (W1+W3+W4+D + AE + O)	0.7674	7.00 %	0.4831
Window 1+ Door + Ambient environment + Orientation (W1+D + AE + O)	0.7669	6.93 %	0.5196
Window 2+ Window 3+ Air conditioning + Ambient environment + Orientation (W2+W3+AC + AE + O)	0.7664	6.87 %	0.4939
Window 1+ Window 3+ Ambient environment + Orientation (W1+W3+AE + O)	0.7664	6.87 %	0.5324
Window 1+ Window 4+ Air conditioning + Ambient environment (W1+W4+AC + AE)	0.7656	6.74 %	0.4970
Window 3+ Window 4+ Ambient environment + Orientation (W3+W4+AE + O)	0.7654	6.73 %	0.4803
Window 1+ Window 2+ Air conditioning + Ambient environment + Orientation (W1+W2+AC + AE + O)	0.7653	6.70 %	0.5057
Window 1+ Window 4+ Door + Ambient environment + Orientation (W1+W4+D + AE + O)	0.7653	6.70 %	0.5289

those based on single spatial factors alone. Specifically, all the top combinations identified in the analysis included W and AE, with the majority also including O. This indicates that these factors make a prominent contribution to improving the accuracy of predictive models. As discussed in the previous section, when individually considering AE or O, the increase in prediction accuracy was only 0.28 % and 1.41 %, respectively. However, when considering AE + O, the model accuracy increased by 3.01 % to 0.7388. This indicates that the integrated consideration of AE and O had a better impact on improving the accuracy of models compared solely to considering AE or O.

In addition, the model considering W1+W3 had an accuracy increase of 1.62 %, while the model considering W1+W3+AE + O had a greater increase in accuracy of 6.87 %. Similarly, the model considering W3+W4 had an accuracy increase of 1.29 %, whereas the model considering W3+W4+AE + O had a significant increase in accuracy of 6.73 %. The average RMSE value of the models considering multiple variables was 0.5074, which was lower than the mean value of those considering a single variable (0.5674). These results highlight the impact of the combination of multiple spatial factors on model accuracy, where the whole was greater than the partly considerated cases.

Moreover, the variables for air conditioning and doors appeared separately in the top ten combinations, each one in four separate instances, and a total of eight occurrences in the top ten, indicating that they are important in the model development but do not necessarily need to be considered in combination.

5.2. The influence of healthcare-related parameters

5.2.1. The influence of combinations considering healthcare-related variables

As shown in Table 5 and Fig. 11, not only did solely considering healthcare-related factors decrease prediction accuracy in comparison to the baseline model, but these models also had a higher RMSE value compared with the baseline model. Among these models, the single consideration of HR performed best, with an accuracy of 0.7144 (0.39 % lower than the baseline). This is followed

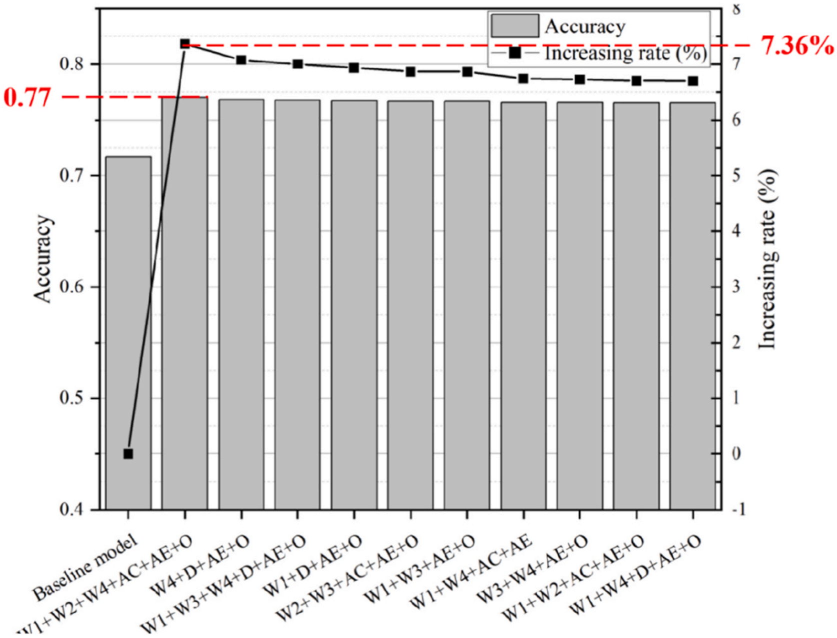

Fig. 10. The prediction results of Top 10 combination of spatial variables.

Table 5
The results of combinations considering healthcare-related variables.

Combination	Accuracy	SC value	RMSE
Baseline model	0.7172	0.00 %	0.5937
Body temperature (BT)	0.7073	−1.38 %	0.6110
Heart rate (HR)	0.7144	−0.39 %	0.6042
Blood pressure (BP)	0.6999	−2.40 %	0.6300
Medical treatment (MT)	0.7082	−1.26 %	0.5835
Body temperature + Heart rate (BT + HR)	0.7033	−1.93 %	0.6187
Body temperature + Blood pressure (BT + BP)	0.7088	−1.18 %	0.6092
Heart rate + Blood pressure (HR + BP)	0.7082	−1.25 %	0.5995
Heart rate + Medical treatment (BT + MT)	0.7054	−1.64 %	0.5622
Body temperature + Medical treatment (HR + MT)	0.7097	−1.04 %	0.6107
Blood pressure + Medical treatment (BP + MT)	0.7010	−1.01 %	0.5836
Body temperature + Heart rate + Blood pressure (BT + HR + BP)	0.7076	−1.33 %	0.6164
Body temperature + Heart rate + Medical treatment (BT + HR + MT)	0.7134	−0.53 %	0.5978
Body temperature + Blood pressure + Medical treatment (BT + BP + MT)	0.7068	−1.45 %	0.5830
Heart rate + Blood pressure + Medical treatment (HR + BP + MT)	0.7051	−1.69 %	0.5949
Body temperature + Heart rate + Blood pressure + Medical treatment (BT + HR + BP + MT)	0.7079	−1.29 %	0.5827

by individually considering MT and BT, with accuracies of 0.7082 and 0.7073, respectively. The inclusion of BP, however, decreased prediction accuracy the most, scoring 0.6999 (2.4 % lower than the baseline model) while the RMSE value increased to 0.63. Overall, most of the combinations that consider multiple healthcare-related variables had a higher prediction accuracy than any single consideration, except for HR. Similarly, the RSME increased with these single considerations. Among these combinations, BT + HR + MT had the best performance with an accuracy of 0.7134, which was 0.53 % lower than the baseline model.

5.2.2. *Top ten combinations of spatial and healthcare-related parameters*

Table 6 and Fig. 12 show the prediction accuracy and SC value of those ten models with the highest prediction accuracy out of the 32,767 combinations when considering combinations of spatial and healthcare-related parameters. To investigate the contribution of healthcare-related parameters, the prediction accuracy of models without considering these parameters have also been displayed in Table 6. It is apparent that the integrated consideration of spatial and healthcare-related variables has a significant impact on increasing prediction accuracy compared with the baseline model. Furthermore, the involvement of healthcare-related parameters improves the positive effect of the spatial parameters. As discussed above, the combination of W2, W3, W4, AE, and O achieved a prediction accuracy of 0.7562. However, when BP was additionally considered, the accuracy increased to 0.7753. This indicates that the inclusion of BP increased the prediction accuracy of combinations of spatial parameters by 2.53 %. Moreover, this combination had a lower RMSE value (0.5224) than the baseline model. The other nine combinations also demonstrated good prediction performance by increasing accuracy by more than 7.13 %, with the lowest RMSE value also decreasing to 0.4496. After comparing with

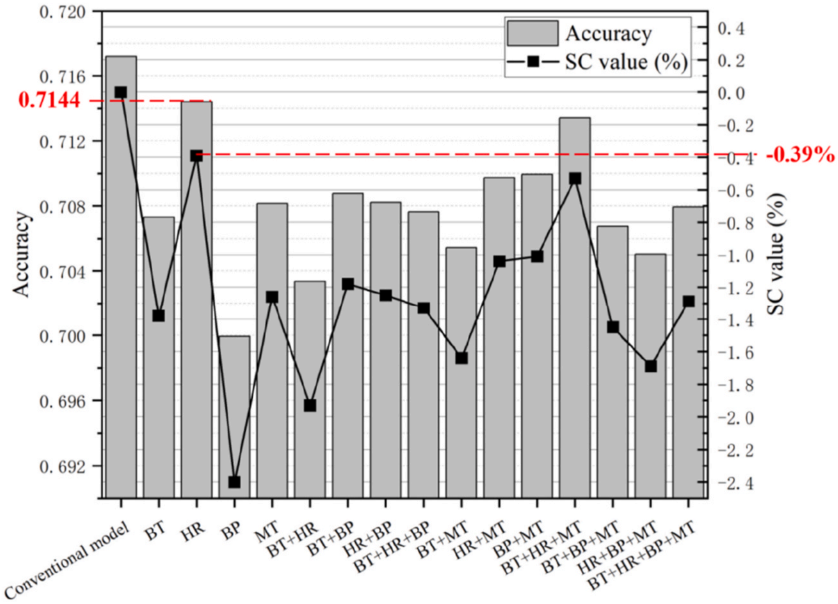

Fig. 11. The prediction accuracy of combinations among healthcare-related variables.

Table 6
The combinations among spatial and healthcare-related parameters with Top 10 accuracy.

Combination	Accuracy	SC value to the baseline model	SC value to models without healthcare-related parameters	RMSE
Baseline model	0.7172	0.00 %	0.00 %	0.5937
Window 2+Window 3+Window 4+Ambient environment + Orientation + Blood pressure (W2+W3+W4+AE + O + BP)	0.7753	8.10 %	2.53 %	0.5224
Window 1+Window 3+Window 4+Ambient environment + Orientation + Blood pressure + Medical treatment (W1+W3+W4+AE + O + BP + MT)	0.7747	8.02 %	1.95 %	0.5363
Window 4+Ambient environment + Orientation + Body temperature (W4+AE + O + BT)	0.7718	7.61 %	1.83 %	0.4496
Window 1+Window 3+Window 4+Air conditioning + Ambient environment + Orientation + Blood pressure (W1+W3+W4+AC + AE + O + BP)	0.7699	7.35 %	5.56 %	0.5781
Window 2+Window 3+Door + Air conditioning + Ambient environment + Blood pressure + Medical treatment (W2+W3+D + AC + AE + BP + MT)	0.7698	7.34 %	2.92 %	0.4948
Window 1+Window 3+Window 4+Ambient environment + Heart rate + Blood pressure + Medical treatment (W1+W3+W4+AE + HR + BP + MT)	0.7696	7.31 %	1.27 %	0.5200
Window 3+Ambient environment + Orientation + Heart rate + Blood pressure (W3+AE + O + HR + BP)	0.7696	7.30 %	1.03 %	0.4844
Window 1+Window 4+Ambient environment + Orientation + Blood pressure (W1+W4+AE + O + BP)	0.7695	7.29 %	1.18 %	0.5062
Window 1+Window 4+Air conditioning + Ambient environment + Orientation + Heart rate + Blood pressure (W1+W4+AC + AE + O + HR + BP)	0.7692	7.26 %	0.71 %	0.4983
Window 1+Window 3+Window 4+Air conditioning + Ambient environment + Blood pressure (W1+W3+W4+AC + AE + BP)	0.7683	7.13 %	1.71 %	0.5160

combinations that only consider spatial parameters, the involvement of healthcare-related parameters in these combinations also contributes to enhancing the prediction accuracy. The inclusion of healthcare-related parameters improved the prediction accuracy of the model without these parameters by a maximum of 5.56 %, with an average increase of approximately 2.1 %. As displayed in Table 6, BP was included in most of the top ten models, indicating that it had a significant effect on improving the model. MT appeared in three of the top six combinations, suggesting that it also had a positive effect on the prediction accuracy of the model.

5.3. *The influence of outdoor weather*

Table 7 and Fig. 13 display the average prediction accuracy and SC values of models considering the top ten combinations discussed above and outdoor weather (OW). To investigate the impact of OW, the prediction accuracy of models without considering OW have also been displayed in Table 7. It was found that the sole consideration of OW decreased prediction accuracy to 0.7023, which was 2.08 % lower than the baseline model, while the RMSE value also decreased to 0.4977. Nevertheless, combinations of OW with spatial and healthcare-related variables performed better than the baseline model in terms of prediction accuracy. However, OW played a

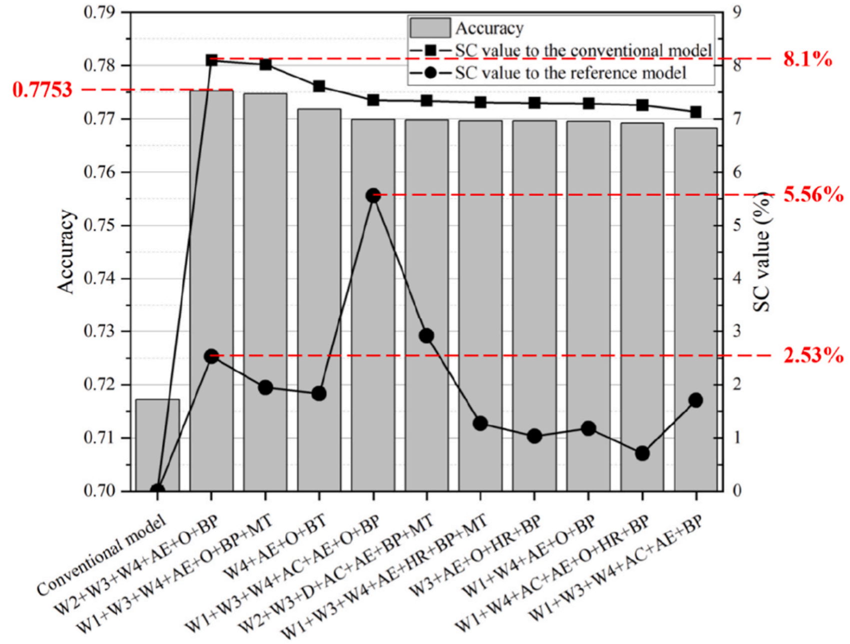

Fig. 12. The prediction accuracy of combinations among spatial and healthcare-related parameters with top ten accuracy.

Table 7
The results of personal thermal sensation predication model considering outdoor weather.

Combination	Accuracy	SC value to the baseline model	SC value to models without considering OW	RMSE
Baseline model	0.7023	−2.08 %	−2.08 %	0.5937
Window 2+Window 3+Window 4+Ambient environment + Orientation + Blood pressure + Outdoor weather (W2+W3+W4+AE + O + BP + OW)	0.7665	6.88 %	−1.13 %	0.4977
Window 1+Window 3+Window 4+Ambient environment + Orientation + Blood pressure + Medical treatment + Outdoor weather (W1+W3+W4+AE + O + BP + MT + OW)	0.7542	5.16 %	−2.65 %	0.4892
Window 4+Ambient environment + Orientation + Body temperature + Outdoor weather (W4+AE + O + BT + OW)	0.7451	3.89 %	−3.46 %	0.5002
Window 1+Window 2+Window 4+Air conditioning + Ambient environment + Orientation + Outdoor weather (W1+W2+W4+AC + AE + O + OW)	0.7536	5.08 %	−2.13 %	0.514
Window 1+Window 3+Window 4+Air conditioning + Ambient environment + Orientation + Blood pressure + Outdoor weather (W1+W3+W4+AC + AE + O + BP + OW)	0.7574	5.61 %	−1.62 %	0.5198
Window 2+Window 3+Door + Air conditioning + Ambient environment + Orientation + Blood pressure + Medical treatment + Outdoor weather (W2+W3+D + AC + AE + O + BP + MT + OW)	0.7467	4.12 %	−3.00 %	0.4739
Window 1+Window 3+Window 4+Ambient environment + Heart rate + Blood pressure + Medical treatment + Outdoor weather (W1+W3+W4+AE + HR + BP + MT + OW)	0.7511	4.73 %	−2.40 %	0.4375
Window 3+Ambient environment + Orientation + Heart rate + Blood pressure + Outdoor weather (W3+AE + O + HR + BP + OW)	0.7331	2.21 %	−4.74 %	0.4981
Window 1+Window 4+Ambient environment + Orientation + Blood pressure + Outdoor weather (W1+W4+AE + O + BP + OW)	0.7395	3.11 %	−3.90 %	0.4971
Window 1+Window 4+Air conditioning + Ambient environment + Orientation + Heart rate + Blood pressure + Outdoor weather (W1+W4+AC + AE + O + HR + BP + OW)	0.7525	4.93 %	−2.17 %	0.511

detrimental role in improving the accuracy of the top ten combinations considering spatial and healthcare-related parameters. OW results in at least a 1.13 % drop in the prediction accuracy for the top ten combinations of spatial and healthcare-related variables, with the mean RMSE value declining to 0.4939.

5.4. *Top 100 combinations with the highest prediction accuracy*

The number of occurrences and the occurrence rate of each variable in the top three, top five, top ten, top 30, top 50 and top 100 combinations are indicated in Figs. 14 and 15.

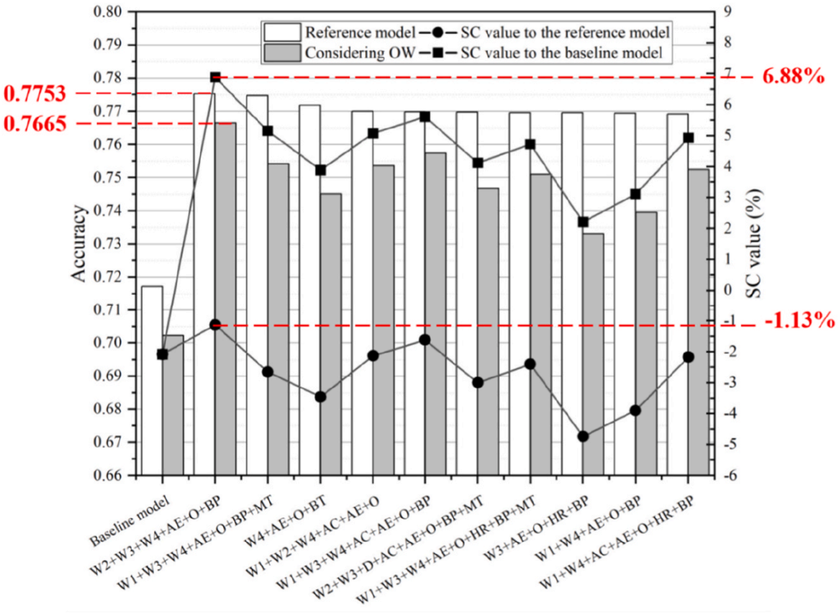

Fig. 13. Results of ANN-based prediction models.

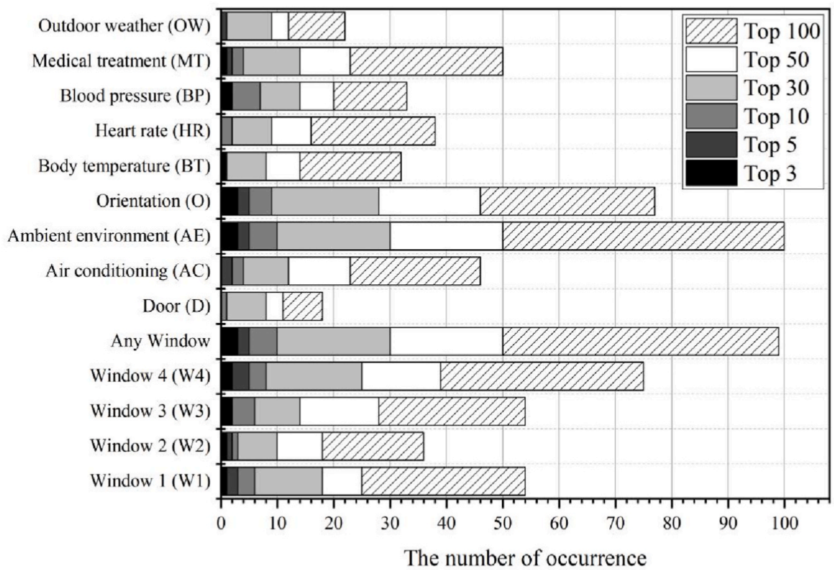

Fig. 14. The occurrence of each variable and combinations in the TOP 100 combinations.

The frequency of AE occurrences was 100 % across all one hundred combinations. O appeared three times in the top three, five times in the top five combinations and 77 times in the top 100 combinations. Individual windows, while infrequent, appeared alternately in these combinations. The combinations considering any of the windows (W) comprised 100 % of the top 50 and 99 % of the top 100. Therefore, AE, O and W were crucial variables in boosting model prediction accuracy. Although AC may not be as statistically significant as AE, O and W, it remained an important influencing factor due to its presence in nearly half of the combinations studied. In addition, BP appeared twice in the top three combinations and seven times in the top ten while MT occurred in the optimal combination and 50 % of the top 100 combinations. Therefore, BP and MT had some effect on the personal prediction model. Despite doing modestly in these 100 combinations, BT was present in the combination with the highest prediction accuracy. Consequently, the impact of BT on the model's evolution cannot be disregarded. Therefore, the spatial impact of windows, ambient environment, room orientation, patients' blood pressure, body temperature and medical treatment should be considered in the ANN-based personal thermal comfort prediction model establishment.

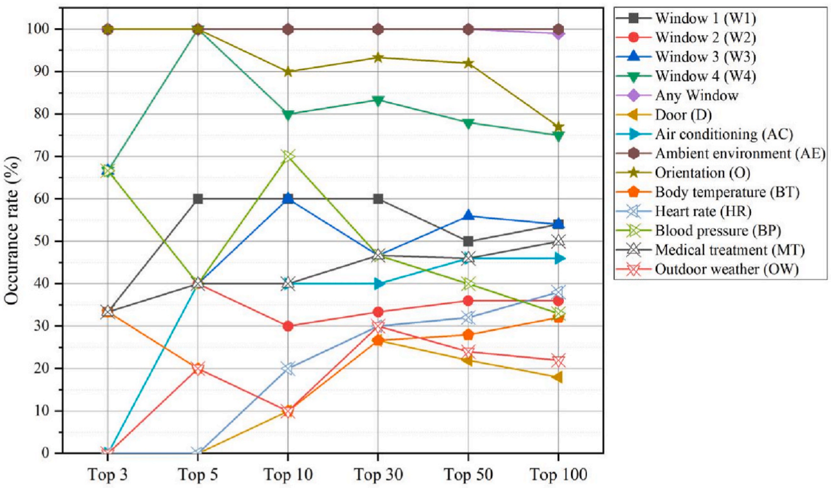

Fig. 15. The occurrence rate of each variable and combinations in the TOP 100 combinations.

5.5. *Verification of the ANN-based prediction model*

Two ML algorithms were chosen for verification in this research, which are Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). Fig. 16 shows the average prediction accuracy and SC values of the five combinations with the highest prediction accuracy by using these different ML algorithms.

The greater the SC value, the greater the improvement in model prediction accuracy. It is clear that incorporating spatial parameters and healthcare-related parameters into the ML-based prediction models has the potential to improve the accuracy. Among these factors, the integrated consideration of windows, ambient conditions, orientation, and subjects' blood pressure had the most significant positive influence in increasing the prediction accuracy of all these ML-based models. Moreover, the ANN-based personal thermal sensation prediction models were more accurate than the SVM-based and KNN-based models.

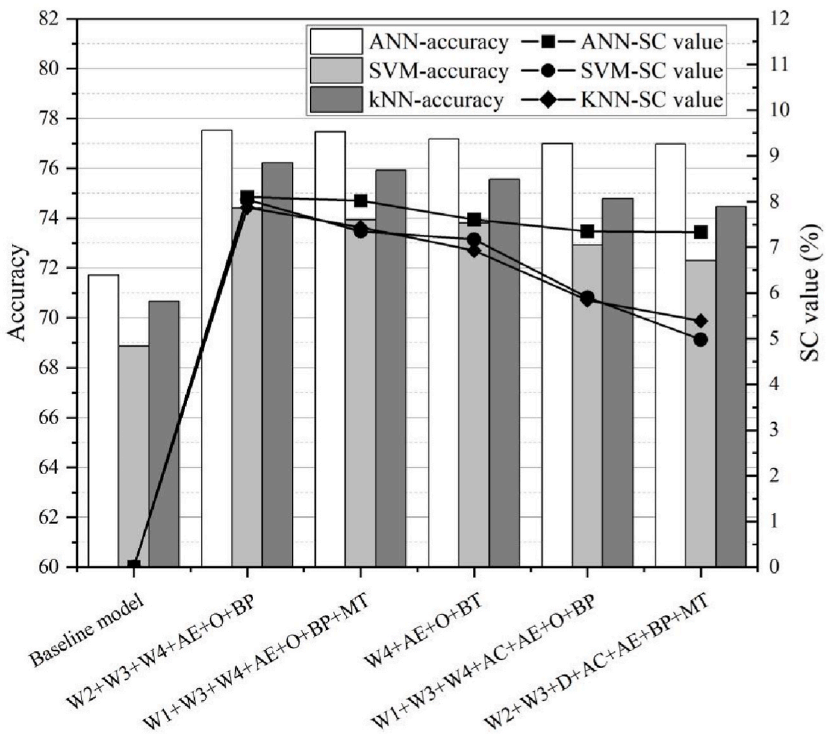

Fig. 16. Results of SVM, KNN and ANN-based prediction models.

6. Conclusions

An ANN-based model has been developed to investigate the parameters that influence patients' personal thermal sensations in healthcare environments. This paper also explored the important impact of spatial and healthcare-related variables on the accuracy of prediction model. The spatial parameters included three-dimensional coordinates of windows, door and air conditioning outlet positioning in the room, together with their surface temperatures, window orientation. Additionally, the ambient environment and room orientation have also been taken into account. The healthcare-related parameters included biosignal variables (body temperature, heart rate and blood pressure) and on-going medical treatment.

The results demonstrate that the ANN-based thermal sensation prediction model performs better than traditional models in processing real-world data from wards, exhibiting higher prediction performance. In addition to the conventional parameters, the incorporation of spatial parameters in the model has a significant impact on model prediction accuracy, particularly when windows (W), ambient environment (AE) and orientation (O) are considered simultaneously. Furthermore, the consideration of subjects' blood pressure (BP) and medical treatment (MT) has a significant impact on increasing the accuracy of the prediction model for orthopaedic rehabilitation patients. Among the top 100 combinations of all influential variables, body temperature and heart rate were found to be crucial to the accuracy of the prediction model.

When developing patients' personalized thermal comfort prediction models in rehabilitation wards, it is important to consider individual differences (i.e. age, gender, and BMI) and conventional parameters in the PMV model (i.e. indoor air temperature, humidity, air speed, mean radiant temperature, occupants' clothing insulation, and metabolic rate). It is also important to consider indoor spatial parameters (i.e. surface temperature and coordinates of windows and air conditioning outlets, ambient environment, and room orientation) and healthcare-related parameters (i.e. blood pressure and medical treatment). By providing more accurate predictions for indoor thermal comfort in healthcare environments, this model can facilitate the design process and enable designers to achieve optimal thermal comfort for patients. This can be achieved by considering adjustments to the thermal environment as well as strategic spatial design factors such as the placement of windows and air conditioning outlets. In addition, this model could provide engineers with more accurate and realistic prediction results. It enables them to develop smart control systems for HVAC that can save energy on one hand and meet occupants' thermal preference on the other.

In future work, it is expected that the size of the dataset will be enlarged. For example, recruiting more patients with various diseases, as they are likely to have different biosignals and medical treatments. Additionally, collecting data in different seasons and healthcare environments with diverse outdoor climates and indoor environments. Moreover, the relationship between indoor thermal environment and hospital-related infections under pandemic should also be considered in future research [52].

Author contribution

Conceptualization, Puyue Gong and Bing Chen; Data curation, Puyue Gong and Yuanzhi Cai; Formal analysis, Puyue Gong and Yuanzhi Cai; Funding acquisition, Bing Chen, Cheng Zhang, and Qichao Ban; Investigation, Puyue Gong and Yuhong Yu; Methodology, Bing Chen and Puyue Gong; Supervision, Bing Chen, Cheng Zhang, Spyros Stravoravdis and Stephen Sharples; Writing-original draft, Puyue Gong; Writing-review and editing, Bing Chen, Cheng Zhang, Spyros Stravoravdis and Stephen Sharples.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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