Exploring an Individual Thermal Sensation Analysis Model for Hospital Inpatients based on Comparative Studies

Abstract

This research investigated the key factors that influenced patients' individual thermal sensations in a rehabilitation ward. Maintaining thermal comfort is important for occupant's well-being in healthcare facilities. The commonly used Predicted Mean Vote (PMV) thermal comfort model has limitations on considering an individual's needs, especially if the individual has impaired health. There was a lack of thermal sensation studies in medical settings. This study conducted a ten-week fieldwork in a real rehabilitation environment in order to develop a thermal sensation analysis model that could help understand individual patient's thermal needs. Traditional statistical models and artificial neural network (ANN)-based models, using real-world data including spatial and healthcare-related parameters, were established for a comparative study.

The results of the study unveiled the substantial influence of spatial and healthcare-related parameters on inpatients' indoor thermal sensations. Furthermore, the ANN-based model demonstrated better performance in aligning with real-world conditions and in providing more accurate prediction outcomes compared to the traditional statistical model. These findings can be used by hospital designers and engineers to optimising the overall quality of the thermal environment within healthcare environment.

Keywords: Individual thermal sensation, Prediction model, Artificial Neural Network (ANN), Healthcare environment, Inpatients

1. Introduction

It is important to improve the indoor thermal environment in healthcare facilities, as it can profoundly affect occupants' health, well-being, and productivity (Tang & Chen, 2021; Pereira et al., 2020; Phiri & Chen, 2014). Maintaining optimal thermal comfort levels for inpatient rooms plays a crucial role in promoting positive emotions and facilitating favourable healthcare outcomes (Shajahan et al., 2019). Previous research in thermal comfort predominantly focused on evaluating the occupants’ average thermal comfort levels, considering factors such as air temperature, relative humidity, air velocity, mean radiant temperature, clothing insulation, and metabolic rate. This approach was originally developed by Fanger (1970), who carried out controlled climate chamber studies using, mainly, healthy individuals such as students. Nevertheless, it has been observed that individuals often exhibit distinct and different perceptions of indoor comfort despite experiencing identical environmental conditions (Zhe et al., 2018). There is an urgent need to develop a more tailored approach to indoor thermal environment design by taking into account "individual differences". Additionally, previous research has indicated that spatial design elements, encompassing orientation, spatial layout design, and occupants' positions, will influence users’ thermal sensations (Du et al., 2016). Furthermore, patients' thermal sensations within inpatient rooms may be affected by their health status and the unique medical environment (Ucinowicz & Bogdan, 2021; Yuan et al., 2022). Patients' underlying medical conditions can affect their thermal physiology, thermal sensation, metabolism, blood flow, and regulatory responses, making them more sensitive to their surroundings compared to individuals in good health (Diller, 2015).

Several models have been established for predicting thermal comfort. The Predicted Mean Vote (PMV) model has been applied extensively in assessing indoor thermal comfort across office buildings, educational institutions, and commercial settings (Fanger, 1970). However, the PMV model fails to consider individual differences (Wang et al., 2018), spatial parameters (Gong et al., 2022), or healthcare-related factors (Del Ferraro et al.,2015; Alotaibi et al., 2020). As a result, the abilities of the PMV model have been found inadequate in predicting individual patient’s thermal sensation (Feng et al., 2022). To address this disparity, researchers have undertaken efforts to develop advanced models that can accurately predict personalised thermal comfort. Among these models, machine learning (ML) has emerged as a promising approach for predicting an individual occupants' thermal sensation. However, prevailing personal thermal sensation analysis models have primarily focused on healthy subjects, while their validation in medical settings remains limited (Uścinowicz & Bogdan, 2021). It is also challenging to exam the indoor thermal sensation in healthcare environments according to the requirements of the ASHRAE-55 standard as patients' distinctive physical and psychological health conditions cannot tolerate intensive or large-range air temperature changes.

To fill in the gaps, this research aims to investigate patients' individual thermal sensation in a real-world healthcare environment by developing an analysis model based on machine learning (ML).

2. The influencing mechanism of thermal sensation

Fiala et al. (1999) proposed two mechanisms that influence thermal comfort: passive and active systems. Specifically, the passive system involves exchanging heat between the human body and the surrounding physical environment through various ways, including heat conduction, convection, radiation, and sweat evaporation. Among them, there are several environmental factors, including air temperature, relative humidity, air velocity, and mean radiant temperature, intricately linked to the occupant's skin temperature, determining occupants' thermal comfort (Kim et al., 2021). In addition, an individual's metabolism plays a crucial role in regulating body temperature through heat generation and transfer via blood circulation (Zhao et al., 2021). While increased metabolism can improve thermal comfort in a stable environment, excessive increases can lead to discomfort (Kim et al., 2021). Moreover, clothing, acting as a barrier between the thermal environment and the skin, can affect the metabolic rate of occupants (Yang et al., 2016; Havenith, 2002), thereby affecting individual occupant's thermal perception. Furthermore, the indoor architectural spatial layout (Du et al., 2016) and room orientation (Caner & Iten, 2020) also influence the ambient environment of occupants, consequently affecting their thermal perception. It is worth noting that Chaudhuri et al. (2017) have demonstrated that outdoor weather conditions can have either a psychological or direct impact on indoor thermal comfort.

The active system encompasses various physiological processes, including vasoconstriction, relaxation, trembling, and sweating, which interact with and impact the passive system (Fiala et al., 2001). It plays a crucial role in regulating human body's core temperature, maintaining it at approximately 36.5 °C through heat output and exchange (Fiala et al., 2001; Gagga et al., 1971). Previous research showed that there was a significant correlation between heart rate and metabolic rate, which impacted the thermal perception of individuals in buildings (Choi et al., 2012; Wilson & Crandall, 2011). Some studies demonstrated that the relationship between indoor temperature and blood pressure was nonlinear (Umishio et al., 2022), while blood pressure exhibited a linear association with human metabolism and activity level (Gilani et al., 2016). In response to an uncomfortable thermal environment, the body often employs peripheral vascular dilation and perspiration to regulate body temperature (Charkoudian, 2016). Additionally, the body elevates heart rate to maintain blood pressure (Schlader and Wilson, 2016).

Variations in gender, age, and body mass index (BMI) also exert an influence on both the passive and active systems (Wang et al., 2018). Previous studies have demonstrated disparities in heat preferences among different age and gender groups (Jiao et al., 2017; Soebarto et al., 2019). Schellen et al. (2010) reported that older adults perceived heat and cold differently compared to younger adults. Furthermore, Katić et al. (2018) have identified that variances in body mass and height can lead to changes in skin temperature, thereby impacting individual’s thermal comfort. The mechanism of passive and active systems has been synthesised and visually represented in Figure 1. In addition, specific medical treatments can influence the thermal sensation experienced by patients in a medical setting. Figure 1 illustrates that massage and acupuncture have been shown to impact on patients' skin temperatures and heart rates (Drust et al., 2003; Huang et al., 2013; Kim, 2021), while infusion treatments can affect their heart rate, blood pressure, and body temperature (Groll et al., 2009). These factors have the potential to influence patients' thermal perception and overall comfort.

Therefore, when investigating patients' thermal comfort, it is crucial to consider individual differences such as age, gender, and body mass index (BMI), along with the specific medical interventions, while concurrently analysing both passive and active systems.

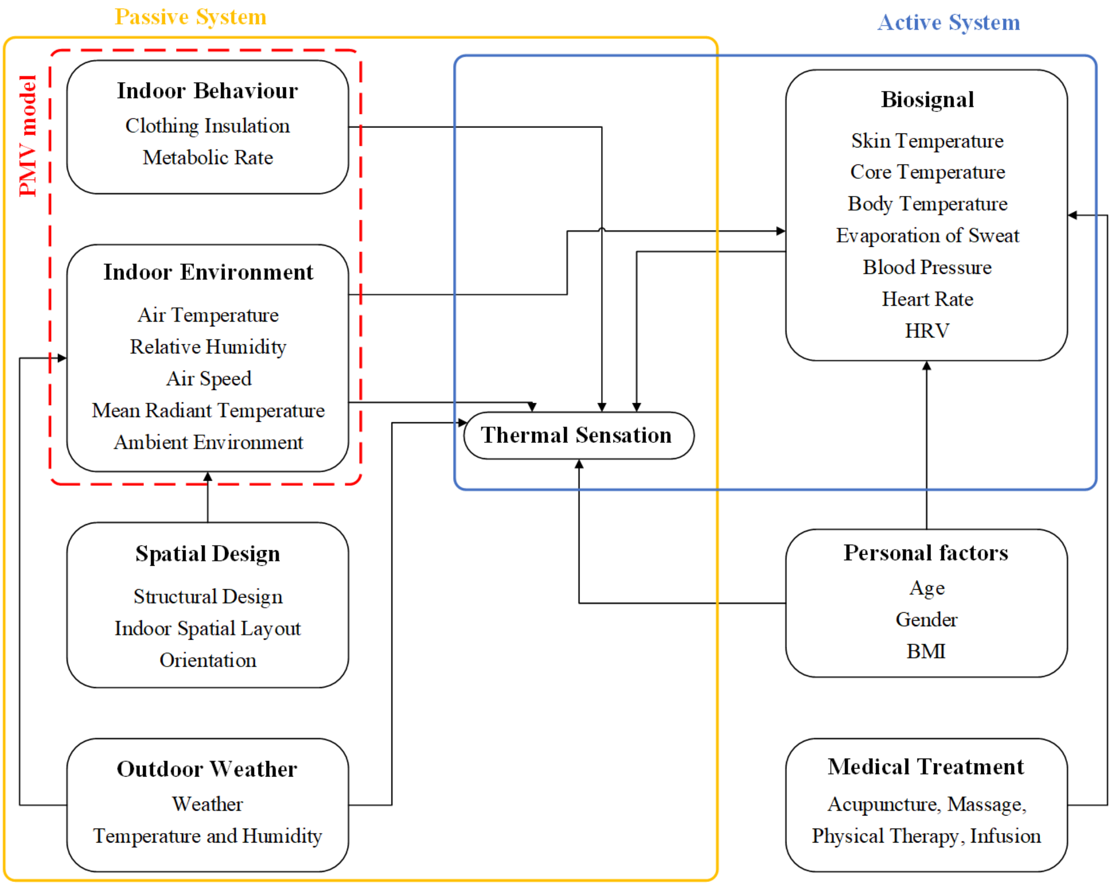

Figure 1 The influencing mechanism of thermal comfort.

3. Thermal sensation analysis model

In comparison to residential and educational buildings, the exploration of indoor thermal comfort in healthcare settings remains limited, and influential factors confirmed in non-medical settings have not been thoroughly validated within healthcare settings (Grassi et al., 2022). The Predicted Mean Vote (PMV) model, introduced by Fanger in 1970, stands as the most widely used assessment model for indoor thermal comfort worldwide. This model encompasses six influential parameters, including air temperature and humidity, air speed, mean radiant temperature, occupant metabolic rate, and clothing insulation. Since its initial application in a medical setting in 1977, the PMV model has been extensively employed to assess patients' thermal comfort levels (Smith & Rae, 1977). However, many studies have revealed inconsistencies between the predicted results of the PMV model and the actual thermal sensations reported by patients (Feng et al., 2022). For instance, researchers at an Italian health centre found that the PMV model underestimated the subjects' actual thermal sensations (Fabbri et al., 2019). This discrepancy primarily arises from the fact that the PMV model was based on data obtained from healthy adults, without considering the unique physiological characteristics of patients (Lan & Lian, 2016). Moreover, the PMV model fails to account for the special physical conditions of patients (Ciabattoni et al., 2015).

To improve the accuracy and effectiveness of thermal comfort prediction models, researchers have increasingly proposed data-driven prediction models, with machine learning (ML) emerging as a prominent approach (Feng et al., 2022). ML presents features such as self-learning, rapid computation, and intricate issue resolution (Qian et al., 2020; Wang et al., 2020). ML has demonstrated superior performance in developing models for predicting personal thermal comfort in schools, offices, and residential environments, with some scholars suggesting that ML-based thermal comfort prediction is on average 40% more accurate than the PMV model (Kim et al., 2018; Cosma & Simha, 2018). This was further verified in recent research which found that the PMV model's prediction accuracy for personal thermal comfort levels reached only 27.63%, which was 43% lower than the ML-based model (Gong et al., 2023; Gong et al., 2022).

Moreover, ML is well-suited for handling non-standard and nonlinear relationships (Wang et al., 2020). Several studies have utilised machine learning algorithms to establish personalised models that account for individual diversity. For instance, Katić et al. (2020) employed Support Vector Machines (SVM), Boosted Trees, Bagged Trees, and RUSBoost Trees to establish personalised models in an office building, achieving a mean accuracy of 0.84 using RUSBoosted trees. In another study by Lu et al. (2019), various factors, including skin temperature and clothing surface temperature, were considered during the development of individual thermal models in a school. The study utilised Random Forest (RF) and SVM, and the linear kernel SVM-based model achieved an impressive accuracy exceeding 97%.

Artificial neural networks (ANNs) have demonstrated exceptional performance in predicting thermal sensation vote outcomes (Qian et al., 2020). Shan et al. (2020) proposed an ANN-based model for predicting personal thermal comfort using the average skin temperature of occupants, achieving an average prediction accuracy of 89.2%. Furthermore, Gong et al. (2022) incorporated spatial impact into an ANN-based prediction model, yielding prediction results superior to those obtained with K-Nearest Neighbors (KNN) and SVM. However, it is important to note that these prediction models have not yet been validated in healthcare settings, and establishing such models has not adequately considered healthcare-related parameters, such as bio-signals and medical treatment.

Therefore, it is crucial to incorporate additional healthcare-related parameters and spatial parameters into the inpatient's personalised comfort model and to validate them in healthcare environments.

4. Research Methods

A methodology has been formulated to incorporate spatial parameters and healthcare-related parameters of inpatients into the personal thermal sensation analysis model (Figure 2).

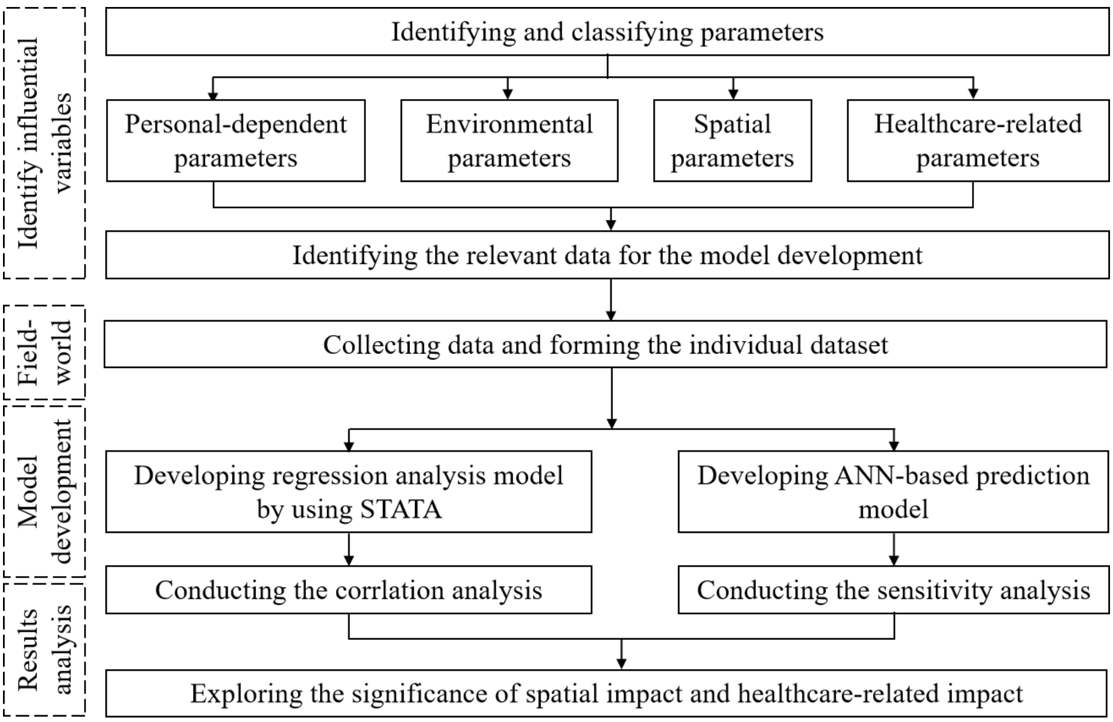

Figure 2 The proposed methodology.

The methodology comprised of four stages: (i) identifying parameters for model development, (ii) conducting fieldwork, (iii) developing the model, and (iv) analyzing the results. In the first phase, parameters were categorised into four groups: personal-dependent parameters, indoor and outdoor environmental parameters, spatial parameters, and healthcare-related parameters (Table 1). Real-world conditions guided the selection of data used for model development.

Subsequently, fieldwork was carried out to gather the necessary data.

Individual datasets were compiled and utilised during the model development phase to establish a regression analysis model using the statistical software STATA (STATA, 2023). Correlation analysis was conducted to explore the significance of spatial and healthcare-related factors on inpatients' thermal sensation. Additionally, an ANN-based model was developed for predicting personal thermal comfort. The model's prediction accuracy, and the impact of spatial parameters on its accuracy, were investigated. The sensitivity coefficient (SC) was calculated to determine the relative importance of individual and combined influential variables on the prediction model (Gong et al., 2022; Gong et al., 2023). Finally, the influential variables that had a significant impact on subjects' thermal sensations were summarised.

Table 1 Parameter identification and classification (adopted from Gong et al., 2022; Gong et al., 2023).

<table>
<tr><th>Categories</th><th>Features</th><th>Description</th></tr>
<tr><td rowspan="4">Personal-dependent parameters</td><td>Subject's basic information</td><td>Age, gender and BMI</td></tr>
<tr><td>Metabolic rate</td><td rowspan="2">Obtained by using ASHRAE-2010</td></tr>
<tr><td>Clothing insulation level</td></tr>
<tr><td>Bedding insulation level</td><td>According to Liu et al. (2021), various types of bedding materials have different thermal insulation values. Specifically, a no cover provides a thermal insulation value of 0.9 clo, while a blanket has a higher value of 1.65 clo. A thin quilt offers even better insulation with a value of 1.98 clo, and a thick quilt provides even more warmth with a value of 2.7 clo. If the thick quilt has more than one layer, its thermal insulation value increases to 3.38 clo.</td></tr>
<tr><td rowspan="2">Indoor environmental parameters</td><td>Indoor environment</td><td>Average indoor air temperature, humidity and air speed</td></tr>
<tr><td>Mean Radiant Temperature</td><td>Calculated by using ASHRAE-2010</td></tr>
<tr><td>Outdoor environmental parameters</td><td>Outdoor weather</td><td>The outdoor temperature, humidity, and weather conditions were recorded. The weather conditions were categorised as follows: sunny (1), cloudy (2), overcast (3), and rainy (4), respectively.</td></tr>
<tr><td rowspan="2">Spatial parameters</td><td colspan="2">Surface temperature of windows, doors and heat sources</td></tr>
<tr><td>Location</td><td>Statistical model: The frequently active locations of the subjects were marked as indicated in the displayed Figure 3, as</td></tr>
</table>

		STATA software cannot recognise three-dimensional coordinates (STATA, 2023). ML-based model: The distances of subjects to windows, doors, and heat sources in three dimensions (X-axis, Y-axis, Z-axis) (Gong et al., 2022).
	Orientation (O)	The window orientation, whether facing north or south, was specifically recorded as (N) for northward and (S) for southward.
	Ambient environment (AE)	The air temperature and relative humidity
Healthcare-related parameters	Personal biosignal	A report for monitoring health on a daily basis, which includes information about body temperature, heart rate, and blood pressure (both systolic and diastolic).
	Medical treatment	The medical treatments given during the data collection periods were documented in the following manner: absence of treatment (0), acupuncture (1), physical therapy (2), massage (3), and infusion (4).

5. Fieldwork

5.1 Study area

The fieldwork took place in Xuzhou, which was situated in Eastern China at 33° 43′–34° 58′ N, 116° 22′–118° 40′ E. Xuzhou experiences a monsoon climate with four distinct seasons. In Xuzhou, air conditioning units are the main source of cooling during the summer. The research fieldwork was conducted throughout the region's regular summer months, from July 1 to September 3. During the experimental period, the average outdoor air temperature was 29.9 °C, ranging from 21 to 37 °C. Various weather patterns, including sunny, cloudy, gloomy, and rainy, were present during the experiment.

5.2 Experiment settings

The research took place in the rehabilitation department of a hospital, located on the fifth floor of a five-story hospital building. The experiment was conducted across eleven wards, comprising of four rooms facing north and seven rooms facing south. All wards had identical layouts, consisting of three inpatient beds, one bathroom, four windows, one door, and an air conditioner. The size of the northern rooms was 3.93 m × 9.09 m × 2.8 m, while the southern rooms was 3.93 m × 9.9 m × 2.8 m. Additionally, all the rooms had a window-to-wall ratio of 0.487 (Figure 3).

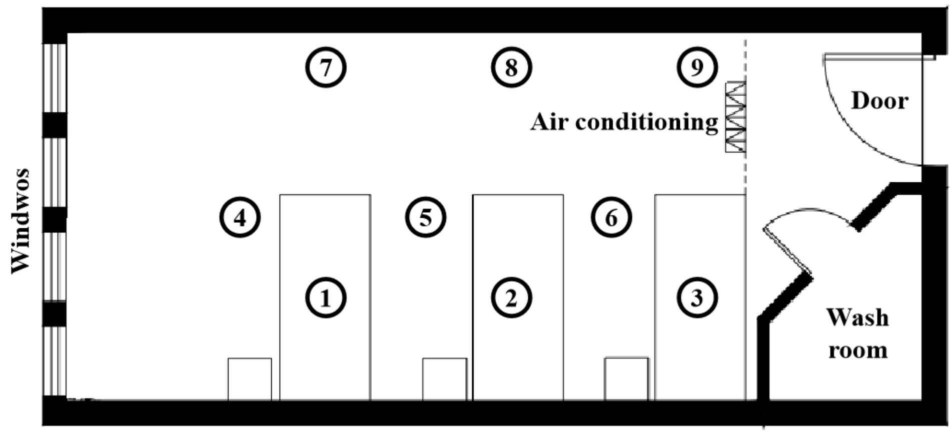

Figure 3 Layout and locations of subjects in an inpatient room

As show in Figure 4, the indoor air temperature was measured using six digital thermometers, each set at a height of 1.1 m. Kim (2017) states that the forehead's skin is most susceptible to temperature variations. Thus, three extra thermometers were placed adjacent to the patients' pillows, aligned with their foreheads when lying down, in order to measure the ambient air temperature throughout the study. The coordinates of the windows, doors, air conditioning outlets, and the centre points of the subject sites were also recorded.

Figure 4 The experiment ward and relevant monitoring devices.

Xiaomi Bluetooth thermometers were employed to measure indoor air temperature and relative humidity (RH) with a precision of 0.1 °C and 1% RH, respectively. These thermometers had a measurement range of 0% to 99% for RH and 0°C to 60°C for temperature. To assess the surface temperatures of windows, doors, and air conditioners, a FLIR E85 thermal camera was utilised with a measurement range of -20℃ to 120°C, and an accuracy within 2°C. Additionally, Testo 405i anemometers were employed to detect air velocity, which had a measurement range of 0-10 m/s and an accuracy of 0.1 m/s.

5.3 Experimental procedure

Due to impaired physical and psychological conditions, patients in healthcare settings are typically more sensitive to environmental changes than healthy individuals (Ban et al., 2021). Despite ASHRAE guidelines recommending consideration of indoor temperature as a variable in healthcare research, it has been challenging to incorporate this in to practical healthcare settings. This study employed real-world data gathering to collect information about the environment, participants, and the results of thermal sensation voting without the influence of the surrounding environment. Personal information, including age, gender, BMI, and daily health data, such as body temperature, heart rate, and blood pressure, were obtained from the participants' clinical records. Additionally, the positions of patient beds, air conditioning outlets, windows, and doors were recorded before the fieldwork.

Four data collection activities were conducted daily at 9:00 am, 12:00 pm, 2:00 pm, and 4:00 pm, respectively. During each data collection time, various factors were noted, including the insulation level of participants' clothing and bedding, their metabolic rate, indoor relative humidity and temperatures at different locations, indoor wind speed, and the subjects' ongoing medical treatments. The thermal sensation level of patients was regularly assessed using the ASHRAE 7-point thermal sensation voting scale, ranging from -3 (cold) to 3 (hot) (Figure 5). However, it is worth noting that the majority of participants were individuals over 60 years old, with reading and vision difficulties. The authors did not provide additional instructions or information that could potentially influence the outcome; instead, they read each participant's thermal sensation voting questions. The air temperature and relative humidity were recorded during each data collection slot.

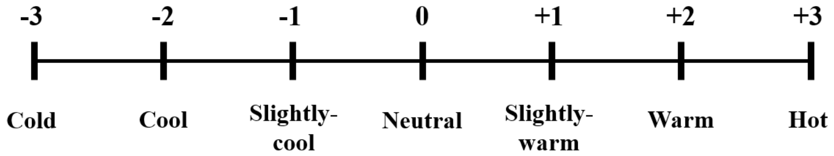

Figure 5 ASHRAE Thermal Sensation scale (ASHRAE, 2021).

5.4 Subjects

All patients in the experimental wards who had neurological rehabilitation issues and demonstrated autonomous consciousness were recruited during the experimental period. Ultimately, twenty-seven Chinese patients, comprising six females and twenty-one males, were willing to participate in the data collection and were selected as participants for the study. Their ages ranged from 46 to 85, and they presented with various neurological conditions, including 7 cases of cerebral haemorrhage, 12 cases of cerebral infarction, 5 cases of hemiplegia, 1 case of carotid-cavernous fistula infarction, 1 case of thalamic haemorrhage, and 1 case of extracerebral haemorrhage. The participants also had different types of neurological disorders. On average, they stayed for 20.9 days.

5.5 Academic ethics consideration

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

6. Traditional statistical analysis model

6.1 Regression analysis model

A total of 1,304 unique thermal comfort votes were collected during a 10-week data collection period. These datasets were analysed using multiple linear regression analysis conducted with STATA MP-17 software (STATA, 2023), which had been widely used in environmental,

behavioural, and evidence-based studies (Chen et al., 2013). Multiple linear regression analysis is a statistical technique that is widely used in indoor thermal comfort studies to explore relationships between different parameters and thermal comfort perception (Oseland, 2005; Humphreys, 1975). This approach has also been used to analyse the effects of influential variables, such as clothing insulation, relative humidity, air velocity, radiant temperature, and metabolic rate, on occupants' thermal sensations (Oseland, 2005; Brager & de Dear, 1998).
The correlation analysis performed in this study aimed to explore the effects of each significant variable on the level of thermal comfort experienced by patients in a real-world inpatient room, as well as the interactions between these variables. Initially, the investigation focused on factors included in the Predicted Mean Vote (PMV) model, including air temperature, relative humidity, airspeed, mean radiant temperature (MRT), clothing insulation, and metabolic rate (MET). Person-specific information, such as age, gender, and body mass index (BMI), was also considered. Spatial variables were considered, including the location and surface temperature of windows, doors, and air conditioning, as well as ambient environment and orientation. The locations of the individuals were represented by markers, as shown in Figure 3. Furthermore, healthcare-related variables were also considered, including patients' body temperature, heart rate, blood pressure (both systolic and diastolic), and medical interventions.

6.2 Partial correlation analysis

Partial correlation is indicated to be useful when interactions among multiple independent variables exist, as in multiple regression analysis (Hair et al., 2010). Therefore, a partial correlation analysis was conducted using STATA MP, and the findings are presented in Table 2.

Table 2 Partial correlation results.

Variable	**Partial corr. (r)** ***(B-value)***	**Significance value** ***(p-value)***
Age	-0.0864	0.002**
Gender	-0.1455	<0.001***
BMI	0.2263	<0.001***
Clothing insulation	0.1353	<0.001***
MET	0.0663	0.0177

Medical treatment	0.0374	0.181
Body temperature	0.0247	0.3766
Heart rate	-0.0202	0.4698
Systolic blood pressure	-0.0058	0.8368
Diastolic blood pressure	-0.0567	0.0426**
Weather	-0.041	0.1423
Temperature	-0.0133	0.6344
Humidity	-0.0217	0.4384
Air speed	-0.0922	0.001***
MRT	0.0191	0.4957
Location	0.0402	0.151
Surface temperature_W1	-0.0207	0.4592
Surface temperature_W2	0.0542	0.0525*
Surface temperature_W3	-0.0304	0.2768
Surface temperature_W4	0.0328	0.2415
Surface temperature_door	0.0002	0.994
Surface temperature_air conditioning	-0.0874	0.0017**
Ambient temperature	0.2836	<0.001***
Ambient humidity	0.1447	<0.001***
Orientation	0.0087	0.7566

(*** denotes statistical significance at $p< 0.01$; ** denotes statistical significance at $p< 0.05$; * denotes statistical significance at $p< 0.1$; and the parameters highlighted in bold present whose *p-value* is less than 0.1.)

Table 2 displays the partial correlation coefficients, squared values of the partial correlation coefficients, and p-values for each variable.

The results indicate that the subject's age, gender, BMI, clothing insulation, air speed, air conditioning outlet surface temperature, ambient temperature, and ambient relative humidity significantly correlated with their thermal comfort sensation (p<0.001). Clothing insulation showed a positive regression coefficient (B=0.1353) with a significant level (p<0.001), suggesting that, as clothing insulation increases, the thermal sensation level increases. Furthermore, BMI exhibited a positive coefficient (0.2263), indicating that individuals with higher BMI may have a higher level of thermal comfort. On the other hand, age showed a negative correlation with thermal sensation (B=-0.0864, p=0.002), indicating that younger subjects were more tolerant of cold environments than older subjects. Gender displayed a negative coefficient (-0.1455), suggesting that, on average, female respondents had lower thermal comfort levels than their male counterparts when all other variables in the model were consistent. Moreover, airspeed has a negative correlation with thermal sensation (B= -0.0922, p=0.001), which means that higher airspeeds from the air conditioning gave the subject a cool feeling. In addition, MET had a positive coefficient (0.3441) and a moderate p-value (0.018), indicating that as MET increases, the thermal comfort level also increases.

The abovementioned variables were fundamental factors covered by the PMV model and existing personal thermal comfort prediction models. Moreover, including spatial and biosignal variables revealed significant associations with subjects' thermal sensation, underscoring their noteworthy relationship with thermal comfort. Specifically, the surface temperature of the air conditioning outlet displayed a negative coefficient (-0.0874) and a low p-value (0.0017), indicating that, as the air conditioning temperature decreased, the level of thermal comfort decreased. Additionally, ambient temperature and humidity exhibited positive coefficients of 0.2836 and 0.1447, respectively, implying that occupants perceived a greater sensation of heat as these factors increased. Furthermore, the study identified the subjects' diastolic blood pressure as a significant variable affecting thermal comfort (p<0.05). Specifically, diastolic blood pressure was found to have a stronger impact on thermal comfort compared to systolic blood pressure. However, further investigation is required to explore the extent of bio-signal influence by incorporating other bio-signal information and a larger sample size. Regarding the influence of windows on thermal comfort, the study found that the second window from the west had a significant impact (p=0.053), although differences in impact among windows could not be fully explored. Consequently, the study concludes that the surface temperature of windows indeed plays a role in human thermal comfort.

In summary, the ambient temperature and humidity, blood pressure of patients, as well as the surface temperature of windows and air conditioning outlets, demonstrated a significant correlation with thermal sensation in rehabilitation wards. Therefore, when establishing a predictive model for the personal thermal comfort of rehabilitation patients, it is important to consider these variables.

7. ANN-based prediction model

7.1 Establishment of ANN-based prediction model

An ANN-based model for predicting individual thermal comfort was developed based on the fieldwork data, as depicted in Figure 6. The model incorporated conventional parameters (i.e., age, gender, BMI, clothing insulation, metabolic rate, average air temperature, humidity, air speed, and mean radiant temperature) commonly found in existing personal thermal sensation prediction models. In addition to these parameters, spatial parameters and patients' healthcare-related parameters were incorporated into the ANN-based model. Specifically, the spatial parameters considered in the study encompassed surface temperature, windows, doors, air conditioning outlets, and room orientation. In contrast to the statistical model, the representation of these variables in the context of spatial parameters involves the utilisation of three-dimensional coordinates to denote their respective locations. Conversely, the patients' healthcare-related parameters encompassed bio-signals (e.g., heart rate, body temperature, and blood pressure) and medical treatments received by the inpatients (e.g., acupuncture, physical therapy, massage, and intravenous drips).

A baseline model was established for comparison to assess these parameters' relative impact on the prediction accuracy of ANN-based models. The baseline model included the aforementioned nine conventional parameters. In contrast, the ANN-based model incorporated all nine parameters of the baseline model while additionally incorporating one or more spatial and healthcare-related parameters, either individually or in combination.

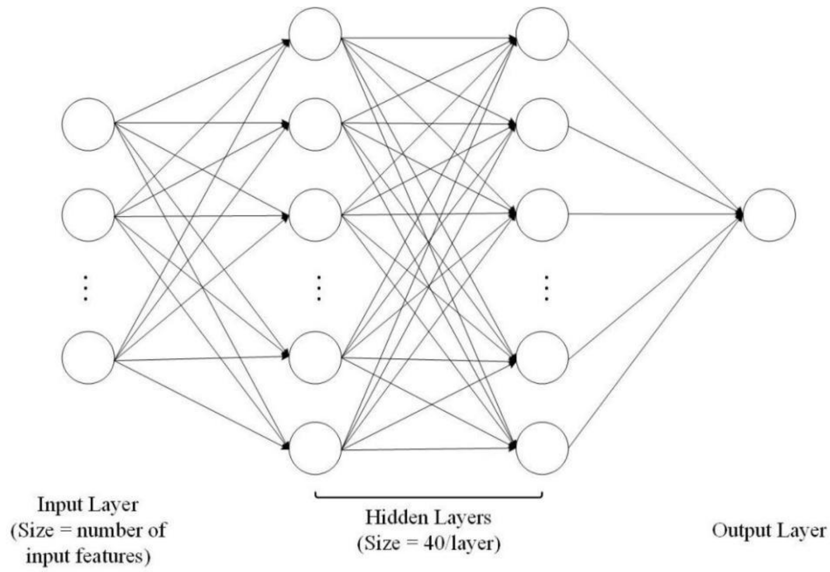

Figure 6 The end-to-end artificial neural network structure (Gong et al. 2023).

Figure 6 illustrates the overall structure of the four-layer ANN employed in this study. The ANNs consisted of an input layer, two hidden layers, and a classification output layer. The number of nodes in the input layer corresponded to the number of input features (i.e., 40), while the number of nodes in the output layer corresponded to the 7-scale thermal sensation. The configuration of the ANNs, such as the number of hidden layers and nodes per layer, was carefully selected to achieve a balance between prediction accuracy and computational efficiency. The study revealed that the prediction accuracy of the ANNs reached a plateau with the current size. While a slight increase in the size of the ANNs led to a minor improvement in prediction accuracy, it significantly increased the processing time. As a result, the selected size of the ANNs was considered to be the optimal choice, striking a balance between prediction accuracy and processing time. For the activation function, the rectified linear unit (ReLU) was utilized, while the loss function employed was cross-entropy. To train the Artificial Neural Network (ANN), the dataset was randomly partitioned into a training set (70%) and a test set (30%). The scaled conjugate gradient method was utilised to optimise the ANN. To mitigate the influence of randomness caused by weight initialization and dataset partitioning, the performance of each feature combination was evaluated by calculating the average test accuracy over one thousand training sessions.

7.2 The impact of influential variables

The comparison among single spatial variables, including windows (which were marked as W1, W2, W3 and W4 from west to east), door (D), air conditioning (AC), ambient environment (AE) and orientation (O), were conducted to explore their impact on prediction accuracy. Among them, the combinations among four windows were discussed as the "single spatial variable" as homogeneous variables.

The average prediction accuracy and SC values of various scenarios were reported in Table 3 and Figure 7 using the traditional model's output as a benchmark. The accuracy of model prediction is increased to a greater extent by larger SC values (Gong et al., 2022). To quantify the disparities between the predicted and actual values, the R^2 (coefficient of determination) and RMSE (Root Mean Squared Error) values were also computed and the results were shown in Table 3. Prediction models are more accurate with a higher R^2 value. On the other hand, the accuracy of prediction models decreases as RMSE increases.

Table 3 The results of the personal thermal comfort prediction model considering the single variable.

Variable	**Accuracy**	**SC value**	**R^2**	**RMSE**
Conventional model	0.7172	0.00%	0.3588	0.5937
W1	0.7008	-2.28%	0.3657	0.5905
W2	0.7127	-0.63%	0.3794	0.5841
W3	0.7245	1.02%	0.3789	0.5843
W4	0.7228	0.78%	0.5100	0.5190
W1+W2	0.7276	1.46%	0.3691	0.5889
W1+W3	0.7288	1.62%	0.3844	0.5818
W1+W4	0.7318	2.03%	0.4925	0.5282
W2+W3	0.7265	1.30%	0.4147	0.5672
W2+W4	0.7243	0.99%	0.4430	0.5533
W3+W4	0.7264	1.29%	0.4084	0.5703
W1+W2+W3	0.7322	2.09%	0.3891	0.5795
W1+W2+W4	0.7271	1.38%	0.4180	0.5795
W1+W3+W4	0.7477	3.01%	0.4408	0.5544
W2+W3+W4	0.7235	0.88%	0.4664	0.5416
W1+W2+W3+W4	0.7330	2.21%	0.4302	0.5597
D	0.7226	0.76%	0.4209	0.5642
AC	0.7286	1.59%	0.4497	0.5642
AE	0.7192	0.28%	0.3820	0.5829
O	0.7273	1.41%	0.4021	0.5733

BT	0.7073	-1.38%	0.3209	0.6110
HRV	0.7144	-0.39%	0.3359	0.6042
BP	0.6999	-2.40%	0.2779	0.6300
MT	0.7082	-1.26%	0.3806	0.5835

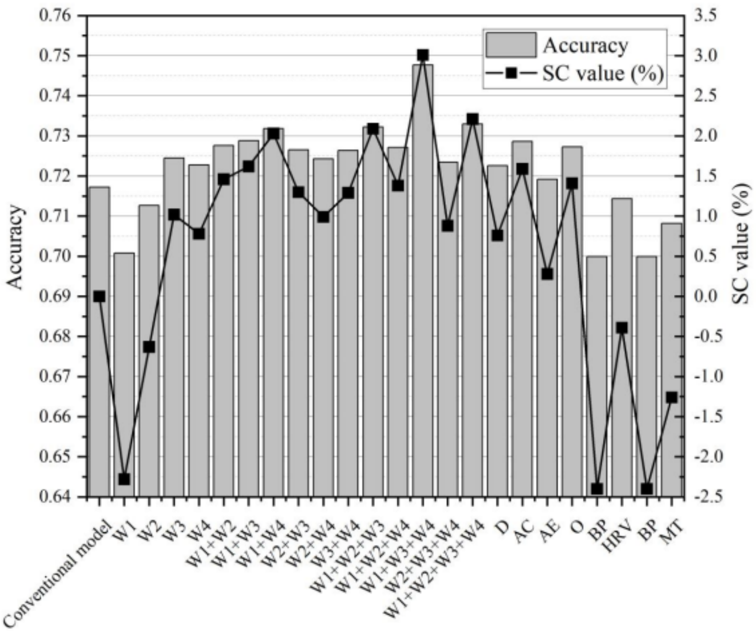

Figure 7 Results of ANN-based prediction models.

Figure 7 illustrates that incorporating spatial variables generally led to improved accuracy in the model's predictions, except for the combination of W1 and W2. When all windows were taken into account, the maximum accuracy achieved was 0.733, which was 2.21% higher than the conventional model. Considering multiple windows together, such as W1+W2+W3 and W1+W4, also resulted in increased precision, with accuracies of 0.7322 and 0.7318, respectively. It was observed that the impact of multiple windows on prediction accuracy was more substantial than that of a single window. The average accuracy for single-window predictions was 0.7152, whereas for multiple-window predictions, it reached 0.7281. The inclusion of AC and O variables also made notable contributions to enhancing prediction accuracy, with accuracies of 0.7286 and 0.7272, respectively. Additionally, the variable D improved prediction accuracy by 0.76%. However, the effect of AE was relatively smaller, resulting in only a 0.28% increase in accuracy compared to the conventional model.

On the other hand, the sole consideration of healthcare-related factors resulted in decreased prediction accuracy compared to the conventional model. Among these variables, HR exhibited the best performance with an accuracy of 0.7144 when considered individually. MT and BT followed with accuracies of 0.7082 and 0.7073, respectively. The inclusion of BP had the most adverse impact, resulting in an accuracy of 0.6999, which was 2.4% lower than the conventional model.

7.3 Combinations among spatial and healthcare-related parameters

In Table 4 and Figure 8, the prediction results of considering combined spatial and healthcare-related variables are displayed. These 10 models were compared with the benchmark models, which simply considered the spatial model without including healthcare-related factors, in order to investigate the impact of occupants' bio-signals and medical treatment on the model improvement.

Table 4 The combinations among spatial and healthcare-related parameters with Top 10 accuracy.

Combination	**Accuracy**	**SC value to the conventional model**	**SC value to the reference model**	**R^2**	**RMSE**
Conventional model	0.7172	0.00%	0.00%	0.3588	0.5937
W2+W3+W4+AE+O+BP	0.7753	8.10%	2.53%	0.5035	0.5224
W1+W3+W4+AE+O+BP+MT	0.7747	8.02%	1.95%	0.4769	0.5363
W4+AE+O+BT	0.7718	7.61%	1.83%	0.6323	0.4496
W1+W3+W4+AC+AE+O+BP	0.7699	7.35%	5.56%	0.3920	0.5781
W2+W3+D+AC+AE+BP+MT	0.7698	7.34%	2.92%	0.5546	0.4948
W1+W3+W4+AE+HR+BP+MT	0.7696	7.31%	1.27%	0.5081	0.5200
W3+AE+O+HR+BP	0.7696	7.30%	1.03%	0.5731	0.4844
W1+W4+AE+O+BP	0.7695	7.29%	1.18%	0.5338	0.5062
W1+W4+AC+AE+O+HR+BP	0.7692	7.26%	0.71%	0.5483	0.4983
W1+W3+W4+AC+AE+BP	0.7683	7.13%	1.71%	0.5157	0.5160

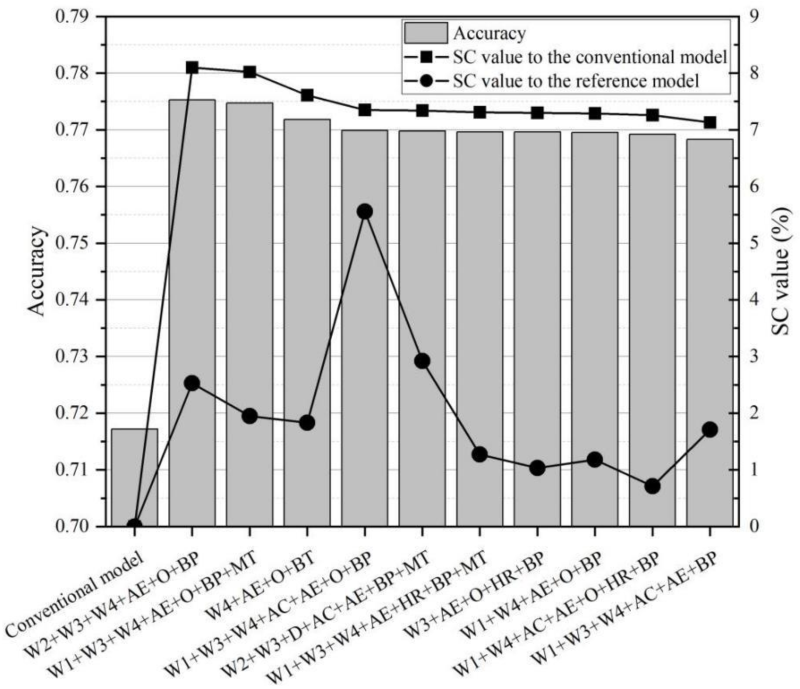

Figure 8 The prediction accuracy of combinations among all parameters with Top 10 accuracy.

Figure 8 illustrates the substantial enhancement in prediction accuracy achieved by integrating spatial and healthcare-related variables, surpassing the traditional model. Furthermore, the beneficial effects of spatial impact were significantly amplified by incorporating healthcare-related variables. The highest accuracy of 0.7753 was achieved when considering variables W2, W3, W4, AE, O, and BP, which represented an improvement of 8.1% compared to the traditional model. Additionally, compared to the conventional model, this integrated approach exhibited a higher R^2 value of 0.5035 and a lower RMSE value of 0.5224.

The subsequent nine combinations also demonstrated notable improvements, yielding an accuracy increase exceeding 7.13% and showcasing robust prediction performance. The highest R^2 value observed was 0.6323, with a reduced RMSE value of 0.4496. Furthermore, including bio-signals within these combinations further enhanced the accuracy of predictions based on geographical impact, resulting in an average increase of approximately 2.1% and a maximum improvement of 5.56%. Among the ten models, BP exhibited the most substantial impact, appearing twice in the top two combinations and nine times in the top ten. Moreover, half of the top six combinations, which yielded the highest model prediction accuracy, were influenced by MT. While BT and HR also exerted some influence on the model, their impact was not as pronounced as that of BP and MT.

In addition to the Top 10 combinations, the study also investigated the Top 100 combinations. This was to explore the number of occurrences and the occurrence rate of each variable in the Top 3, Top 5, Top 10, Top 30, Top 50 and Top 100 combinations, as indicated in Figure 9.

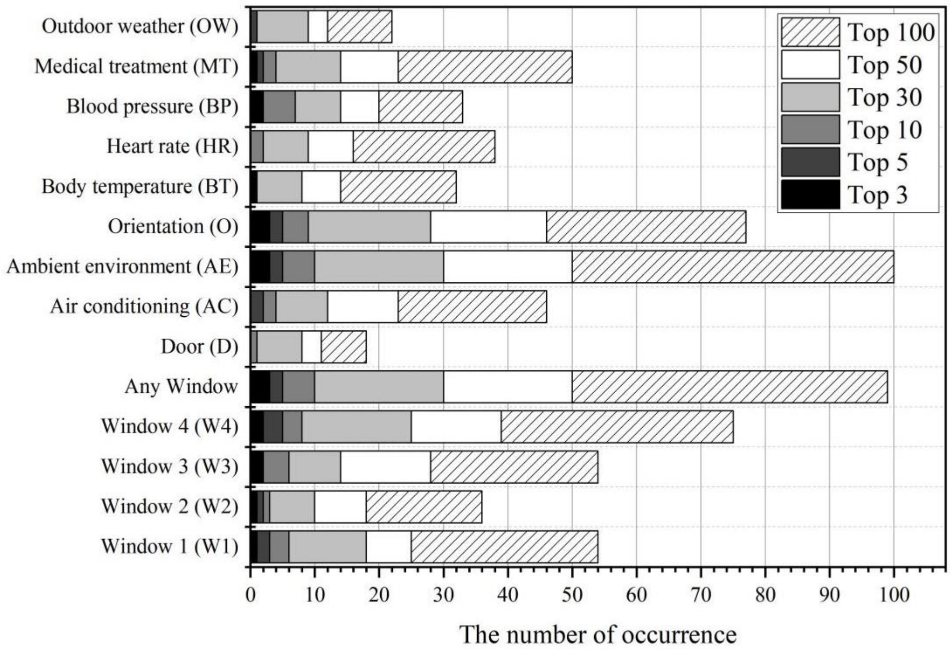

Figure 9 The occurrence of each variable and combinations in the TOP 100 combinations.

Across all 100 combinations, the occurrence of AE was observed in 100% of cases. O appeared three times in the top three combinations, five times in the top five combinations, and 77 times in the top 100 combinations. Although individual windows (W) were infrequent, they appeared in an alternating pattern within these combinations. Notably, the combinations that included any of the windows accounted for 100% of the top 50 combinations and 99% of the top 100 combinations. Hence, AE, O, and W significantly improved the model's prediction accuracy. AC was present in over half of the remaining combinations, despite not being in the top three. Therefore, AC was a highly significant variable in the model's development. Additionally, BP appeared seven times in the Top 10 and twice in the Top 3 combinations. MT was present in 50% of the Top 100 combinations and the ideal combination. Therefore, MT and BP had some influence on the personal prediction model. Although BT's performance in these 100 combinations was poor, it participated in the combination with the best forecast accuracy.

Hence, it is important to consider BT's influence on the model's development.

8. Discussion

Based on the available data, a correlation analysis was conducted to examine the significance of various influential variables on patients' thermal sensations. The findings revealed that spatial parameters (such as ambient temperature and relative humidity, surface temperature of windows, and air conditioning outlets) and inpatients' bio-signals (i.e., blood pressure) had a significant impact on individual's thermal sensation. Subsequently, an ANN-based model was developed, by integrating spatial parameters and healthcare-related parameters, to predict inpatients' individual thermal sensations. The analysis indicated that spatial variables played a crucial role in improving the accuracy of the predictive model. Notably, the presence of windows profoundly affected the performance of personal thermal comfort prediction models, particularly when all windows were considered together. While considering the ambient environment alone had a minimal impact on model development, it made a substantial contribution when examined alongside other spatial parameters. The orientation of the space also had a notable influence on the model's predictive accuracy, especially when evaluated in conjunction with windows and the ambient environment. Although the inclusion of a single biosignal variable did not significantly contribute to model development, the combination of spatial and biosignal variables enhanced the prediction accuracy of personal models. In particular, when combined with spatial variables, blood pressure improved the model's accuracy in establishing a personal thermal comfort prediction model for neurological rehabilitation patients. Additionally, the incorporation of medical treatment had a noticeable impact on enhancing the model's predictive ability.

Both the traditional statistical analysis model and the Artificial Neural Network (ANN)-based prediction model produced similar findings, indicating that spatial parameters and patients' healthcare-related parameters exerted a significant influence on inpatients' indoor thermal sensations. However, unlike the traditional statistical analysis model, the ANN-based prediction model captured the integrated impact of multiple influential variables, including various spatial parameters and combinations of spatial and healthcare-related parameters. Specific parameters exhibited noteworthy significance when considered in conjunction with other variables, highlighting the ANN-based model's capacity to offer more comprehensive and detailed insights into the integrated impact of multiple variables on patients' thermal sensation. In the context of real healthcare environments, interactions among different environmental variables are inevitable (Zhang et al., 2023; Levin & Emmerich, 2013). For instance, the spatial orientation of a room and the window-to-wall ratio have been identified as crucial factors that directly influence the transmission of direct gained solar radiation into the indoor environment, subsequently impacting upon indoor temperature and relative humidity levels (Li et al., 2021). Furthermore, empirical research has demonstrated the significant role of air temperature and relative humidity in sound propagation within indoor spaces (Nowoświat, 2022). Thus, the ANN-based prediction model is better suited for analysing and comprehending the intricate dynamics of real-world conditions.

However, it is important to acknowledge several limitations in this research. Firstly, the dataset used in the study was relatively small, which may restrict the generalizability of the findings to a larger population. Additionally, the collection of on-site data within healthcare environments presented challenges and might have introduced certain biases into the analysis. Having said this, in the context of limited and heterogeneous data, the findings demonstrated that the performance of the analysis model based on ANN surpassed that of the linear regression analysis model. Furthermore, it is crucial to note that this research was conducted in a four-season city during a typical summer, with the subjects specifically being orthopaedic rehabilitation patients. It is worth considering that different diseases may manifest distinct bio-signals and require specific medical treatments. For instance, orthopaedic rehabilitation patients often experience heightened painful thermal sensations (Grzelak et al., 2022). As the number of measurement parameters and the size of the dataset increase, it is possible that the results could benefit from further scrutiny and debate. Furthermore, recruiting a substantial number of subjects and collecting comprehensive data within real-world hospital wards presents considerable difficulties, resulting in an inadequate dataset. Nonetheless, the research findings demonstrate that the use of artificial neural networks (ANNs) can still achieve satisfactory prediction performance with limited data. However, it is imperative to acknowledge that, as the measurement parameters and data size increase, the outcomes of the algorithm may be subject to increased scrutiny and potential challenges over time. Furthermore, owing to the real-world nature of this research, the study encompassed all neurorehabilitation patients possessing self-awareness. Notably, during the study period, the proportion of male patients was significantly higher than that of female patients, reflecting the typical patient distribution observed in neurorehabilitation wards. However, it is worth acknowledging that this study did not extensively delve into the potential impact of gender-specific factors on patient outcomes.

Therefore, future research is expected to address these limitations by conducting investigations with larger sample sizes, encompassing diverse patient populations in various healthcare settings, and accounting for variations across seasons. Additionally, it would be advantageous to incorporate relevant and effective bio-signal variables into the predictive model to enhance its accuracy and applicability.

9. Conclusion

A fieldwork study was conducted to gather real-world data within rehabilitation wards to explore the influential variables affecting patients' personal thermal sensations. Both a regression analysis model and an ANN-based prediction model were developed for this purpose. Findings of this study indicated that both spatial parameters and healthcare-related factors significantly impacted on patients' thermal sensations. Specifically, it was found that spatial parameters, such as windows and the ambient environment, as well as patients' blood pressure, significantly influenced personal thermal sensation. Furthermore, room orientation and the presence of medical staff also demonstrated their contribution to improving the prediction performance of the ANN-based model. Therefore, the development of inpatients' personal thermal sensation analysis model should integrate spatial and healthcare-related parameters.

Moreover, the ANN-based prediction model offers a more comprehensive understanding of the integrated effects of multiple influential variables compared to the traditional statistical analysis model. This characteristic aligns more closely with real-world conditions involving complex interactions among various variables. As a result, this approach significantly aids in the design process and supports designers in attaining optimal thermal comfort for patients. By considering adjustments to the thermal environment and strategic spatial design factors, such as positioning windows and air conditioning outlets, designers can effectively achieve this objective. Moreover, this model offers engineers accurate and realistic prediction outcomes, empowering the development of intelligent HVAC control systems that conserve energy while simultaneously meeting the thermal preferences of occupants. Furthermore, this model also assists medical staff in understanding inpatients' personal thermal preferences, enabling them to arrange the positioning of patient rooms and beds accordingly. As the sample size of hospitals and patients increases, the model can further develop, allowing for the identification of specific thermal design characteristics for different diseases and climate regions. Ultimately, this can influence the development of healthcare environment design standards in the field.

In future work, the dataset is expected to be expanded to encompass a larger sample size. For instance, recruiting a more diverse cohort of patients with varying medical conditions, as different ailments may manifest distinct bio-signals and necessitate specific medical treatments. Furthermore, gathering data from various seasons and healthcare environments that encompass diverse outdoor climates and indoor settings would provide valuable insights.

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