A comprehensive understanding of adaptive thermal comfort in dynamic environments – an interaction matrix-based path analysis modeling framework

A comprehensive understanding of adaptive thermal comfort in dynamic environments - An Interaction Matrix-based Path Analysis modeling framework

Ru Ming [a,b], Baizhan Li [a,b], Chenqiu Du [a,b], Wei Yu [a,b], Hong Liu [a,b], Risto Kosonen [c], Runming Yao [a,b, d,*]

a Joint International Research Laboratory of Green Buildings and Built Environments (Ministry of Education), Chongqing University, Chongqing 400045, China

b National Centre for International Research of Low-carbon and Green Buildings (Ministry of Science and Technology), Chongqing University, Chongqing 400045, China

c Department of Mechanical Engineering, Aalto University, Espoo, 02150, Finland

d School of the Built Environment, University of Reading, Reading RG6 6DB, UK

[*] Corresponding author. Joint International Research Laboratory of Green Buildings and Built Environments, Ministry of Education, Chongqing University, 400045, China.
E-mail address: r.yao@cqu.edu.cn

Abstract:

Human thermal comfort is affected by various interactive variables, revealing the thermal adaptation processes is challenging. Simplifying as a single direct step from triggering factors to assessment, the understanding of interactions and causality among explanatory variables and their link to thermal comfort remains insufficiently explored. An Interaction Matrix-based Path Analysis (IMPA) modeling approach was proposed to examine the direct and indirect effects of variables on thermal comfort and modeling the thermal comfort by combining observed and unobserved factors. To verify the approach, a broader range of variables was investigated in field studies in five climate zones of China. The Back Propagation-Artificial Neural Network (BP-ANN) coding-based interaction matrix described the possible interaction pathways between variables. Based on these interaction pathways and thermal adaptation theory, the results indicated eleven dominant hypotheses with the directed connections. The path analysis modeling method quantified the driving effects and causality between the explanatory variables and thermal sensation under various indoor conditions. It concluded that psychological factors directly affected thermal sensation, while physiological factors displayed an indirect relationship. Environmental and behavioral factors had both direct and indirect effects. Environmental factors contributed the most significant total effects on thermal sensation, followed by psychological and behavioral factors in various environments. The physiological factors had no substantial impact in a neutral environment. The observed variables affecting thermal sensation further underscored the importance of indoor air temperature and thermal expectation. This study could provide new insights into describing the direct and indirect pathways and understanding the thermal adaptation process.

Keywords: thermal adaptation process; path analysis modeling; interactive pathways; direct and indirect effects; observed and unobserved factors

1. Introduction

Over the past century, there has been an increase of about 1.0 °C in global mean ambient temperature [1] and global warming has been identified as a profound universal issue [2]. The current climate emergency has led to a rising realization of the vital role of reducing building energy consumption in mitigating CO_2 emissions [3]. In addition, climate change has exacerbated the problem of increasing levels of thermal discomfort and the widespread health risks to vulnerable persons in overheated buildings, which brought the buildings themselves to the forefront of this challenge [4, 5]. The provision of thermal comfort for occupants in the built environment is a significant use of energy; therefore, understanding and predicting human thermal comfort is a critical feature of research.

Based on the concept of interpreting the interaction between occupants and the indoor climate as a heat balance via convection, conduction, radiation, and latent heat, Fanger proposed the PMV-PPD model considering four environmental parameters and two personal comfort factors [6]. The concept states that to feel comfortable, a thermal equilibrium must exist between the interacting human body and the environment. As defined by the PMV model, six variables affect thermal sensation: four physical variables (air temperature, air velocity, relative humidity, and mean radiant temperature), and two personal variables (clothing insulation and metabolic rate). The steady-state thermal comfort theory did not demonstrate a good match with users' perceptions in naturally ventilated buildings as the physiological and psychological factors are overlooked. This specific limitation of the PMV model has promoted the emergence of adaptive thermal comfort models [7, 8].

As an alternative framework, the adaptive thermal comfort theory states that occupants' thermal comfort obtained in a dynamic environment is the product of active adaptation and hence affected by multiple factors[9, 10]. There is no doubt that environmental factors, including indoor and outdoor environmental factors, have a significant influence [11, 12]. These active adaptation strategies included physiological aspect (e.g. vasoconstriction/vasodilation, sweating, shivering), behavioral aspect (e.g. putting on/taking off clothing, opening/closing the windows, switching on/off a fan or an air conditioner), and psychological aspect (e.g. thermal history and thermal expectation). From then on, the adaptive model was introduced into international thermal comfort standards for naturally ventilated buildings [11, 12]. Following statistical analysis of the data gathered from field studies, several variants of PMV have been proposed, such as the ePMV [13], eSET [14], and aPMV [9] indices. In these updated models, explanatory factors which were not incorporated into the standard PMV model were usually introduced to replace psychological and behavioral adaptation. However, an in-depth examination of the thermal adaptation mechanism is necessary to explain the differences between the heat balance model and the adaptive thermal comfort models.

Thermal adaptive theory proposes that thermal adaptation can be explained by behavioral, psychological, and physiological adaptation [15]. To quantify the influence of these three categories on human thermal comfort, Liu *et al*. [16] introduced the analytic hierarchy process (AHP) method to quantify the weights of the behavioral, physiological, and psychological portions of the adaptation process. The results revealed that the physical environment is critical for guaranteeing occupants' thermal comfort. However, the results provided by the AHP approach were subjective since they were derived by expert scoring. Jing *et al*. [17] incorporated the thermal adaptation process into general system theory and applied the approach of information entropy to quantify the relationships of the three thermal adaptation processes. In their research, the entropy of Clo, TSV, and SCV was used to assess behavioral, psychological, and physiological adaptations, respectively. Behavioral and psychological entropies were derived from field surveys, whereas data on physiological entropy was obtained from laboratory experiments. However, whether these three parameters can be used to describe various adaptation processes is debatable, and the effect of different factors can hardly be compared based on varying sets of data. Schweiker and Wagner [18] modified the clothing insulation and metabolic rate factors to represent the three adaptive processes, and the three weights can be characterized by examining the values of the coefficients in their equations. It was a good attempt to unravel the effects of individual adaptive processes on thermal comfort but ignored the intractable complexity of thermal expectations. A quantitative comparison of each explanatory factor’s influence on adaptive thermal comfort is also an excellent way to explain the “black box”. The ASHRAE Database offers a once-in-a-lifetime ability to investigate and compare various variables using a single dataset [19]. Wang *et al*. [20] classified the data of the ASHRAE Global Thermal Comfort Database into three categories (individual factors, building characteristics, and geographical factors) and utilized univariate regression to analyze the influence of each factor on thermal comfort. The results indicated that local climate has the most significant impact on the neutral temperature, whilst building type and local climate have the most marked influence on thermal sensitivity. However, the majority of existing studies on human thermal comfort describe the individual effects of state variables statistically and the influence on comfort was simplified as one step within the triggering factors that direct assessment. Few studies examined the indirect effects that differ from the cause-effect process, making it a challenge to study thermal adaptation mechanisms systematically.

The regulation of thermal comfort is conceptualized as a systematic process involving the direct causal relationship of explanatory variables with thermal perception (direct effects), as well as their influences on other variables that further affect thermal perception (indirect effects). To provide a holistic view of the causal relationships, structural equation models were first applied to the thermal comfort field in 2017. This revealed the interrelationships between environmental parameters, physiological factors, psychological factors, thermal acceptability, and thermal comfort [21]. Based on the Structural Equation Modeling (SEM) approach, Path Analysis (PA), Latent Class Path Models (LCPM), and Multilevel linear models (MLM) were developed to expand and integrate a conceptual framework that took into account both direct and indirect effects [22-25]. This framework threw light on the contribution weight of each variable on human thermal comfort, considering the comprehensive action among dependent variables and between dependent and independent variables. However, the path analysis method fits multiple linear regression equations based on an assumption about each variable's relationship, which requires experts with empirical knowledge to draw the architecture of the models. This process is subjective thereby increasing the predictive uncertainty of thermal comfort models.

This research aims to describe the holistic pathways between various observed, unquantifiable factors and adaptive thermal comfort through objective analysis to illuminate the "black box" of thermal adaptation and improve the prediction of human thermal comfort. To achieve these objectives, this research developed a modeling framework to model the direct and indirect links between building information, physical environmental parameters, behavioral parameters, psychological parameters, physiological parameters, and adaptive thermal comfort in the real environment. It is conceptually built on the path analysis models, which describe the direct and indirect relationships between different factors. In addition, a larger range of factors was utilized in the analysis, including the observed and unobserved variables. It is important to account for the unobserved factors properly, because they could change the correlations between the driving factors and outcomes. This modeling approach is critical to finding answers to crucial research concerns about ‘exploring the “black box” of thermal adaptation’. The current study differs from the existing studies on thermal comfort prediction and can provide new insights into understanding adaptive thermal comfort processes.

2. Methodology

Path analysis is a particular case of structural equation modeling that examines the causal relationships between the dependent and independent variables by transforming the causal influences to direct and indirect effects [26]. The path analysis method is widely used in statistics, sociology, computer science, transportation engineering, geographic information science, and other fields and has gradually been applied in thermal comfort research in recent years [21, 22, 24, 27-29]. The traditional path analysis method presupposes a relationship between variables in a model based on professional knowledge, followed by the combination of multiple multi-linear regression equations according to the assumptions. To overcome the inherent disadvantages of the path analysis method due to its subjectivity, this study combined the interaction matrix with the path analysis method and proposed the Interaction Matrix-based Path Analysis (IMPA) modeling framework. The methodology is divided into three steps, and an overview of the framework is described in Fig. 1.

Formulating the relationships between variables is a critical starting point for constructing a model [30]. The human thermal comfort response process can be regarded as a complex system [17]. The factors and variables involved may have a specific effect on other factors, even on the whole system. Therefore, an analysis of the occupants' thermal comfort state should use a coupled method that considers the interaction of different factors. Dominated by systems theory, the interaction matrix approach can be applied to analyze the associated mechanisms involving multiple parameters in a project. The essence of this approach is a top-down method that considers the potentially relevant variables, characterizes the essential parameters, and clarifies the interaction mechanisms [31]. In this study, carrying out the path analysis and constructing the interaction matrix using the generic interaction matrix (GIM) enhances the evaluation of the weighting of the parameters within the system. In addition, we used BP-ANN as a coding method of GIM to analyze multidimensional interactive data effectively [32]. (***Step 1***)

The design of an appropriate architecture is essential for a further analysis of the models. The interaction relationship between variables derived from the interaction matrix can determine the precise structural routes, bypassing the limitations of requiring expert empirical knowledge for drawing model architectures. For example, if the interaction matrix results in variable A having a significant effect on variable B, a directed line of A to B can be obtained. All the pathways are connected to the overall model architecture. (***Step 2***)

Path analysis modeling is intended to provide insights into the distribution of each explanatory variable. This study uses interaction matrixes to correct the false statements caused by data aggregation and confounding factors in the previous path model, which quantifies the interaction between the measured variables from an objective perspective and filters out irrelevant variables. Maximum Likelihood Estimation (MLE) is used to calculate the estimates. (***Step 3***)

In this study, the IMPA method was used to quantify the interactive relationships of the variables that contribute to human adaptive thermal comfort. Compared with traditional statistical methods using correlation analysis, the advantage of the present method lies in its capability to comprehensively consider the interactions between variables. Another significant advantage allows a clear description of the influence pathways and the conducting of causal analysis.

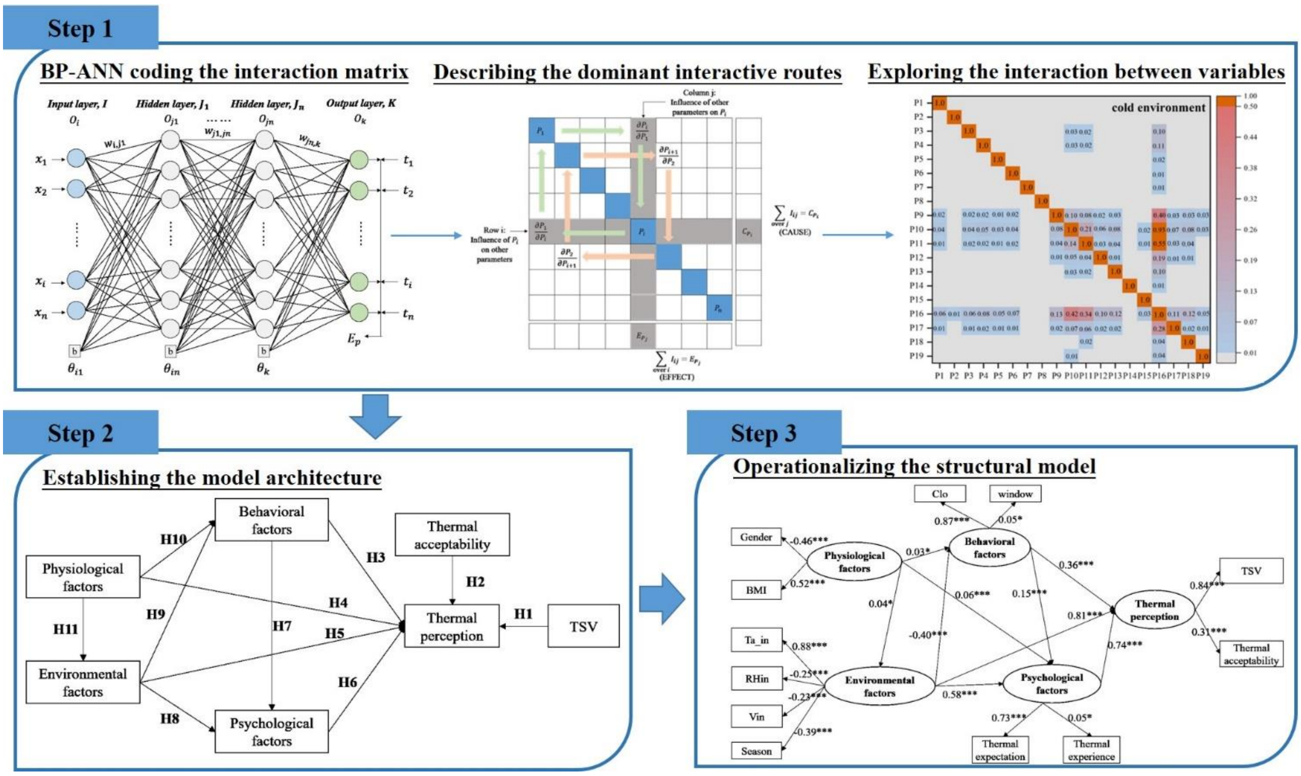
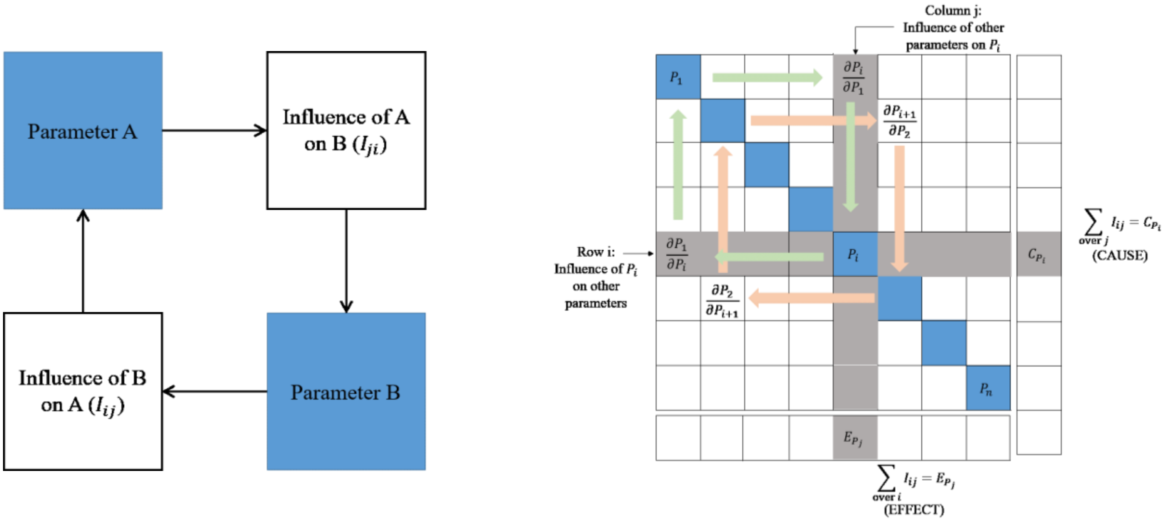


Fig. 1. Conceptual framework and process of the Interaction Matrix-based Path Analysis (IMPA) modeling method.

2.1. Quantification of the interaction between variables

The feature of the interaction matrix lies in treating all the adaptive thermal comfort elements as a complete and interactive system. In the interaction matrix, the factors and variables are arranged on the leading diagonal of the matrix (from the top left to the bottom right). The off-diagonal positions represent the interaction mechanism between variables. The off-diagonal terms are assigned numerical values to indicate the degree of influence that one variable exerts on the others. The matrix rotates clockwise to indicate the direction of parameter interactions. Therefore, the interaction matrix reflects all coupled components and their action paths. Fig. 2 exhibits the schematic diagram of the interaction matrix. As a generic example, Fig. 2(a) shows a simple 2 × 2 matrix with two variables; here, the influence of ‘A’ on ‘B’ is different from the influence of ‘B’ on ‘A’. The general form of the interaction matrix coding is presented in Fig. 2(b). From the matrix construction, the row passing through P_i expresses the effects of P_i on the other variables in the system. At the same time, the column through P_i represents the influences of the other parameters on P_i. It should be noted that there is no limit on the number of variables involved in an interaction matrix.



(a) (b)

Fig. 2. The principle of interaction matrix, (a) two parameters interaction matrix; (b) a general form of the interaction matrix [33].

To obtain the numerical values of the interaction matrix, serval coding methods from a simple decision to a complete numerical analysis were proposed: 1) 0-1 binary method, 2) expert semi-quantitative (ESQ), and 3) continuous quantitative coding (CQC) [34]. However, the common point of these coding methods was that they were determined based on the non-objective intuition of experts. The ANN is also a top-down analysis model decomposing the system into components, which means it is similar to the interaction matrix and reasonable to apply in the interaction matrix method. Therefore, employing the strong learning ability of the ANN, it is possible to undertake complex non-linear mapping from the input parameters to output parameters, identify the effect of inputs on outputs, and then obtain the interaction matrix containing the fully-coupled influences [34].

Back propagation (BP) is the most common and effective learning procedure used to train the ANN [35-37]. The architecture of BP is a hierarchical design consisting of fully interconnected layers of processing units, including the input layer, hidden layers, and output layer [36]. Each layer can connect to the layers below and above [32]. Fig.3 presents the typical architecture of a Back Propagation Network in the learning stage. It is based on repeatedly adjusting the weights of the connections in the network and propagating back the error from the output layer to the input layer, to minimize the difference between the actual output vector and the estimated output vector [38].

In this study, the inputs (x_i to x_n) represent the explanatory variables of thermal comfort, such as indoor air temperature, relative humidity, etc. As shown in Fig.1, this step aims to describe the interactive relationships between explanatory variables, such as exploring the influence of indoor air temperature on clothing insulation, or the influence of clothing insulation on indoor air temperature. Therefore, the outputs variables (O_i to O_k) are the same as the input variables.

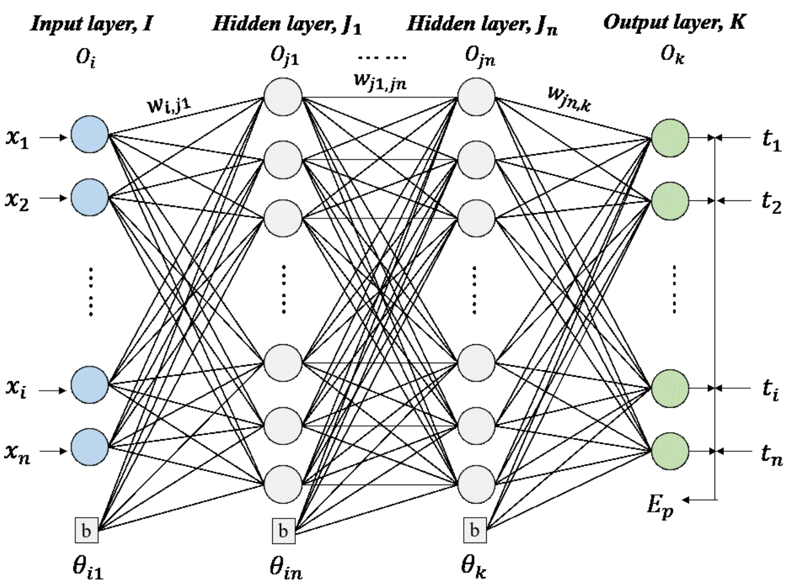


Fig.3. Typical architecture of a Back Propagation Network.

The relative connection weights between input and output layers were used to determine the influence of the inputs on the output. The importance of input and output relationships indicated by the connection weights also demonstrated that the interactions of parameters could be used in the interaction matrix approach [32, 38]. The BP algorithm used in this study plays a role in calculating the first partial derivative of each input node directly for the variations in each output node. On this account, the learning processes were asked to stop, and the network was no longer allowed to adapt once the training was completed. To calculate the derivatives of the neural network, the weights (*W*) and thresholds (*θ*) were supposed to be constant for all current connections. The input and output parameters were normalized at a range of 0 to 1.

An activation function is another important part in the BP architecture, and the Sigmoid function was applied in this paper. In the trained neural network with n hidden layers, the input (*e*) and output (*O*) with the Sigmoid activation function on the layers *I*, J_1 to J_n, and *K* can be written as:

$$O_{j1} = f_{j1}(e_{j1}) = 1/\left(1 + \exp\left(-e_{j1}\right)\right);\ e_{j1} = \textstyle\sum_i O_i W_{i,j1} + \theta_{j1}$$

$$O_{jn} = f_{jn}(e_{jn}) = 1/\left(1 + \exp\left(-e_{jn}\right)\right);\ e_{jn} = \textstyle\sum_{jn-1} O_{jn-1} W_{jn-1,jn} + \theta_{jn}$$

$$O_k = f_k(e_k) = 1/(1 + \exp(-e_k));\ e_k = \textstyle\sum_{jn} O_{jn} W_{jn,k} + \theta_k \tag{1}$$

Where indices *i*, J_n and *K* represent the input units on the output layer *I*, hidden units on the hidden layer J_n, and output units on the output layer K, respectively. $W_{i,j}$ stands for the weighting matrix of the coefficients adjusted for connection between the *i-th* and the *j-th* unit, *f* is an activation function adopted each time, and θ is a threshold of each time.

Since the Sigmoid function is differentiable, the partial derivatives of O_k at output layer *K* concerning O_i at input layer *I* can be calculated as follows:

$$\partial O_k/\partial O_i = (\partial O_k/\partial O_{jn})\,(\partial O_{jn}/\partial O_{jn-1}) \ldots (\partial O_{j2}/\partial O_{j1})\,(\partial O_{j1}/\partial O_i) =$$
$$(\partial O_k/\partial e_k)\,(\partial e_k/\partial O_{jn})\,(\partial O_{jn}/\partial e_{jn})\,(\partial e_{jn}/\partial O_{jn-1}) \ldots (\partial O_{j1}/\partial e_{j1})\,(\partial e_{j1}/\partial O_i) \tag{2}$$

Where O_{jn}, O_{jn-1}, …, O_{j2}, and O_{j1} denote the hidden units in the *n, n-1, …, 2, 1* hidden layer.

The Sigmoid activation function employed in this study can be expressed as:

$$f(\mathrm{x}) = 1/(1 + \exp(-x)) \tag{3}$$

and, the derivative of the Sigmoid function is:

$$\partial f/\partial x = f'(x) = f(x)f(x)\exp(-x) \tag{4}$$

Considering Eq. (1), the derivative at every unit in the hidden layers and output layer is given by:

$$\partial f/\partial x = \exp(-e_k)/(1 + \exp(-e_k))^2 \tag{5}$$

and by

$$G(e_k) = \exp(-e_k)/(1 + \exp(-e_k))^2 \quad (6)$$

Then, substituting Eqs. (5) and (6) into Eq. (2), we have

$$\partial O_k/\partial O_i = \sum_{jn} \sum_{jn-1} \dots \sum_{j1} W_{j_n k} G(e_k) W_{j_{n-1} j_n} G(e_{j_n}) \dots W_{i j_1} G(e_{j_1}) \quad (7)$$

Where O_i represents the explanatory variables of thermal comfort.

It is worth noting that no matter which function is approximated by the neural network, all the items on the right-hand side of Eq.(7) always exist [39], because this process is solved like the differentiation of functions.

Then, introducing a new parameter, Relative Strength of Effect (RSE_{ki}), to define the influence of input unit *i* on output unit *k* according to Eq.(7). For example, $\mathrm{RSE}_{air\ tamperature-relative\ humidity}$ represents the impact of relative humidity on air temperature. The values of RSE_{ki} represent the fully coupled relative influence of each input on each output, which considers all the pathways between two parameters. The corresponding RSE_{ki} values can be computed as:

$$\mathrm{RSE}_{ki} = C \sum_{jn} \sum_{jn-1} \dots \sum_{j1} W_{j_n k} G(e_k) W_{j_{n-1} j_n} G(e_{j_n}) \dots W_{i j_1} G(e_{j_1}) \quad (8)$$

where C is a normalizing constant that limits the maximum absolute value of RES_{ki} to 1, *k* stands for the number of output units, and *i* represents the number of input units.

The RSE_{ki} denotes the strength effect between the interaction matrix's corresponding *i-th* and *j-th* parameters. In addition, the larger the value of RSE_{ki} becomes, the more significant the influence of inputs on outputs. The input has a positive effect on output when $RSE_{ki} > 0$, an adverse action on output when $RSE_{ki} < 0$, and no relation between input and output when $RSE_{ki} = 0$.

2.2. Construction of the path analysis model

The path analysis model is used to estimate the magnitude and significance of hypothesized relationships between thermal comfort and sets of variables related to environmental parameters, behavioral factors, physiological factors, and psychological factors, as well as the direct, indirect, and total effects of those relationships. Using path analysis model building, a causal relationship is established between studied, observed, and latent variables based on a predetermined, three-step model. First, determine the latent variables of the model through theoretical or practical experience or exploratory factor analysis. Then, the observed variables, as determined by the interaction matrix method, are selected to reflect the content of the latent variables. The final step is constructing a theoretical model that explains the causal relationship between measured and latent variables based on relevant theories, knowledge, or experience. Based on the path analysis model, thermal comfort perception is conceptualized as a process in which a person attempts to adjust behavior, physiology, and psychology to adapt to changes in the surrounding environment. The possible relationships and their strengths in this process are the cornerstones for exploring the mechanisms of comfort perception.

2.3. Estimation and evaluation of model parameters

Model estimation refers to estimating model parameters to verify the degree of conformity of the set model with the actual situation. Unlike regression analysis, analysis of variance, and other methods that expect the slightest difference between the estimated value of the model and the actual observed value, the structural equation model predicts the most negligible difference between the covariance matrix of the sample and the covariance matrix implied by the model. Usually, the methods for parameter estimation of structural equation models include maximum likelihood (ML), generalized least squares (GIS), general weighted least squares (WLS), and two-stage least squares (TSLS).

The ML model is the preferred method for estimating fitting parameters and is suitable for situations where the number of samples is large, and the observed data conforms to a multivariate normal distribution. Due to its characteristics of unbiased equivalent estimation and asymptotic normal distribution, this study selects maximum likelihood estimation as the path analysis parameter estimation method.

Six metrics, including the χ^2/df, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), and Comparative Fit Index (CFI), were employed to evaluate the model performance. Table 1 illustrated the fit metrics and their fit criteria.

The AMOS 24 software was utilized to calculate the structural equation models. The AMOS software is based on IBM SPSS, a licensed statistical analysis software. Intuition, speed and convenience are all advantages of this graphically oriented program.

Table 1. Overall model fit index and its fit criteria.

Index	Fit criteria
χ^2/df	1-3 (It increases as the amount of data increases.)
RMSEA	<0.05, fit good; <0.08, acceptable
GFI	>0.09
NFI	>0.09
IFI	>0.09
CFI	>0.09

3. Materials and data

To verify the proposed IMPA modeling method, a variety of variables related to human thermal comfort were collected via field investigations in residential buildings in China's five climate zones: the Severe Cold (SC), Cold (C), Hot Summer and Cold Winter (HSCW), Hot Summer and Warm Winter (HSWW), and Mild (M) regions. Accordingly, the survey buildings were located in the nine typical cities of Shenyang and Harbin in the SC zone, Xi'an in the C zone, Chongqing, Wuhan, and Chengdu in the HSCW zone, Fuzhou and Guangzhou in the HSWW zone, and Kunming in the M zone. The proportions of the surveyed buildings constructed before the '90s and after the '90s were 51.3% and 48.7%, respectively. All the surveyed buildings used a mixed-mode system with neither central heating nor cooling systems, and occupants were free to adapt their clothing, window status, and/or air conditioning. It was worth noting that the buildings located in SC and C regions were supplied with central heating systems in winter, so they were not investigated during the heating season.

Field measurements and subjective questionnaire surveys were conducted monthly in these cities over an entire year providing a complete picture of the annual indoor thermal environment and occupant perceptions. During the survey, indoor and outdoor environmental parameters, such as air temperature, relative humidity, and air velocity, were simultaneously measured. The portable Dwyer 485 data logger (temperature range: -30 °C to +85 C, accuracy: ±0.5 C; humidity range: 0–100%, accuracy: ±2%, Dwyer Company, U.S) and the Testo-425 hot-wire anemometer (range: 0–20 m/s, accuracy: ±0.03 m/s + 5% of measured values, Testo Company) were utilized for collecting the environmental parameters. The quantity and arrangement of measurement points were complied with the prescriptions of the ASHRAE 55 [11]. The measurements were conducted for more than 5 min for each parameter and repeated three times to ensure steady-state conditions [11]. The questionnaire was designed in four parts: the buildings' characteristics, respondents' personal information, the adaptive behaviors and subjective thermal responses to the thermal environment during the test period. The building characteristic information included building location, construction age, and orientation. The respondents' personal information consisted of gender, age, and Body Mass Index (BMI). As for the adaptive behaviors, the clothing adjustment, metabolic rate adjustment, window use, and A/C use behaviors were investigated. Additionally, the thermal experiences and expectations of personnel were examined. The subjective thermal perceptions included the thermal sensation and thermal acceptability. In addition, the raw data was normalized during the collection process. A sample capacity of over 20,000 cases of apartments and occupants was available in the field studies. After removing the vacancies and illogical values, this study recorded 14,116 valid cases of indoor thermal environments and occupants' thermal perceptions.

Adaptive thermal comfort theory proposes that the person is the active agent interacting with his surrounding thermal environment, and human thermal adaptation can be attributed to psychological adaptation, behavioral adaptation, and physiological adaptation [15]. Physiological adaptation consists of the thermal regulation of the human body in a given thermal environment [40-42]. The change in skin temperature, blood pressure, pulse rate, and vasoconstriction/vasodilatation were identified as physiological responses to maintain human comfort and health. Additionally, parameters such as gender, age, height, and weight were also considered as factors that influence physiological responses [15, 41, 43]. Behavioral adaptation is described as conscious or unconscious actions that alter the body's thermal balance, such as putting on/taking off clothing, adjusting the windows, switching on/off cooling or heating equipment, the intake of hot/cold drinks, changes in posture, and slowing down working rhythms [16]. Psychological adaptation involves changes in thermal perception and responses due to past thermal experiences and expectations [44]. Repeated exposure to a specific thermal environment can reduce the thermal sensitivity of the human body, which can later result in changes in thermal expectations. In addition to the three main thermal adaptation processes mentioned above, our previous research describes the complete process of occupant interaction with environmental systems [10]. As shown in Fig.4, physical environment parameters (such as temperature, relative humidity, air velocity), climatic conditions (such as climate type, season, and weather), and building characteristics (such as the building envelope) also affect human comfort and thermal adaptation.

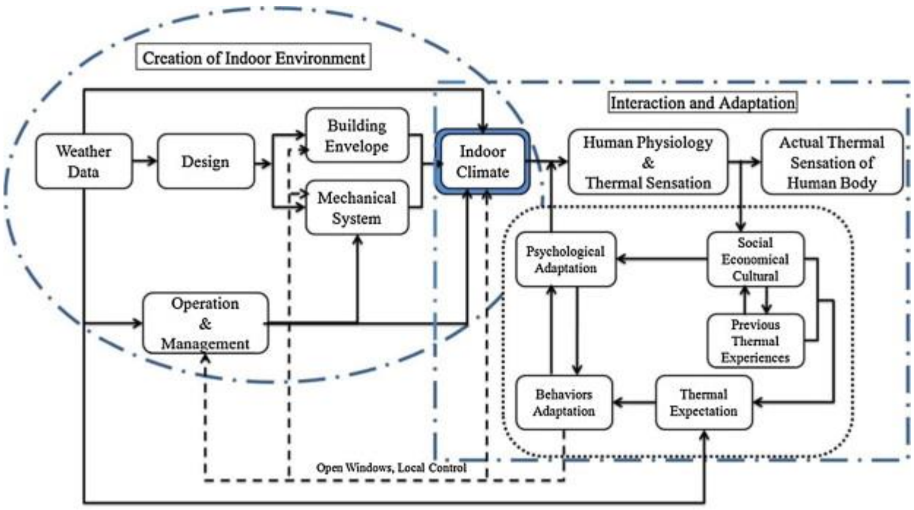


Fig.4. Mechanism of adaptive thermal comfort [10].

In this study, the target variable is TSV, the most commonly surveyed indicator in the thermal comfort assessment [45]. Combined with system theory to consider the coupling effects of various factors, the selection of parameters for human thermal comfort must take into account the impact of various factors in as much detail as possible. Fig.5 illustrates the 19 selected variables, including climatic conditions, building information, physical environmental parameters, physiological parameters, behavioral factors, and psychological factors. Environmental, behavioral, physiological, and psychological variables have been widely used in the literature and are shown to be associated with human thermal perceptions [9]. Climatic conditions directly influence the outdoor environmental parameters and are incorporated into this study. Building information is chosen since it is a link between the indoor and outdoor environment and significantly influences the indoor environment. It should be pointed out that it is challenging to obtain physiological parameters such as skin temperature, vasoconstriction/dilation, sweating, and tremor of subjects during field studies. Even the largest thermal comfort database, the ASHRAE thermal comfort database, fails to cover these parameters, Therefore, the physiological adaptation involved the parameters of gender, age, and BMI. The unobserved variables, such as culture, social, and economic elements, are grouped and placed in the framework of the structural model to analyze the potential effects. The corresponding intervals for each parameter are shown in Table 2.

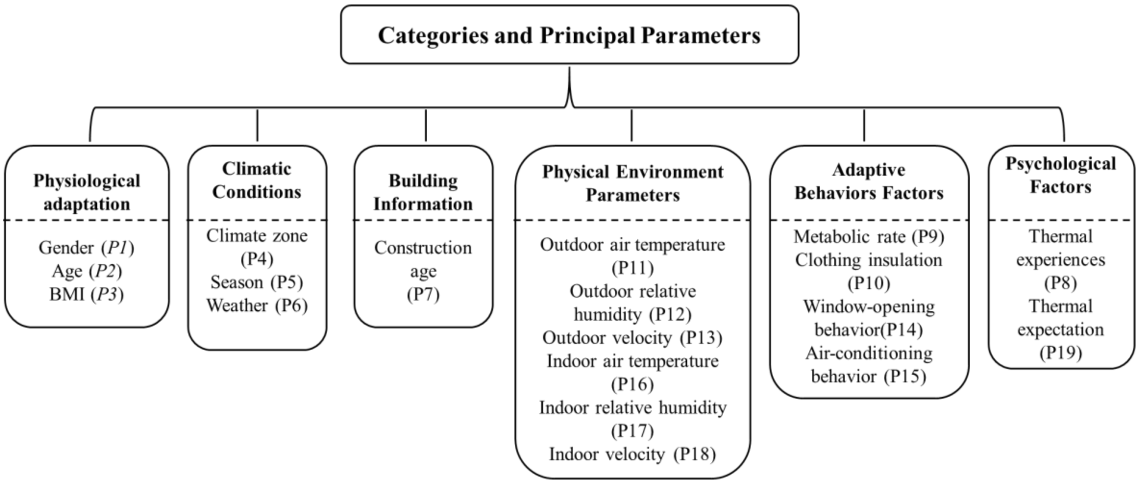


Fig.5. The selected categories and principal parameters.

Table 2

Classification parameters of the system.

Parameter (acronym)	Classification categories and ratings					
1. Gender	Male	Female				
	1	2				
2. Age	< 20 years old	20-30 years old	30-40 years old	40-50 years old	50-60 years old	>60 years old
	1	2	3	4	5	6
3. Climate zone	SC zone	C zone	HSCW zone	HSWW zone	M zone	
	1	2	3	4	5	
4. BMI	Mean=22.74	Max=45.92	Min=11.69			
5. Season	Spring	Summer	Autumn	Winter		
	1	2	3	4		
6. Weather	Sunny	Cloudy	Rainy	Snowy		
	1	2	3	4		
7. Construction age	before the '70s	'70s	'80s	'90s	after	

					2000
	1	2	3	4	5
8. Thermal experience	Mean=24.92	Max=90	Min=0		
9. Metabolic rate	Reclining: 0.8met	Seated: 1.0met	Standing: 1.2met	Walking: 2.0met	
	1	2	3	4	
10. Clothing insulation	Mean=0.69	Max=2.52	Min=0.19		
11. Outdoor air temperature (T_{out})	Mean=18.7	Max=39.5	Min=-6.0		
12. Outdoor relative humidity (RH_{out})	Mean=63.9	Max=99.9	Min=1.8		
13. Outdoor velocity (V_{out})	Mean=0.79	Max=5.0	Min=0.1		
14. Window-opening behavior	Opened-wide	Opened-slightly	Closed		
	1	2	3		
15. Air-conditioning usage behavior	In use	Not in use			
	1	2			
16. Indoor air temperature (T_{in})	Mean=20.1	Max=39.0	Min=1.5		
17. Indoor relative humidity (RH_{in})	Mean=63.5	Max=99.9	Min=2.0		
18. Indoor velocity (V_{in})	Mean=0.09	Max=1.8	Min=0.0		
19. Thermal	Increased	Unchanged	Decreased		

expectation			
	1	2	3

4. Results and discussion

There may be various interactive pathways in different environments. According to the scope of PMV, we defined 3 different environmental conditions: cold (PMV<-1), neutral (-1≤PMV≤1), and hot (PMV>1). The interactive relationships among the explanatory variables and thermal perception in the cold, neutral, and hot environments are revealed in this section.

4.1. The description of interaction pathways

As described in Section 2.1, the BP-ANN method was utilized to code the matrix to elucidate the interaction routes between variables. The central and most challenging aspect of the ANN method was determining the 'optimal' network architecture; in other words, the number of layers and neurons in the hidden layer predicted the performance of the ANN model. In order to find the best artificial neural network structure and achieve the best prediction effect, this study used a genetic algorithm to optimize the structure of a neural network. The neural network structure (the number of neurons in each hidden layer) was taken as the attribute of the individual in the genetic algorithm, and the coding method was decimal coding. The respective optimal network structures from layer 1 to layer 5 were found.

By comparison, it was found that the artificial neural network structure [19,25,25,19] could achieve the best prediction results. This network included an input layer (19 neurons), an output layer (19 neurons), and two hidden layers (25 neurons each). After completing the training process, the first partial derivative of an input node for the variations in each output node can be determined according to Eq.(7), allowing the weights of all relations to be used to measure the interactive variables. The values of off-diagonal elements, driven from Eq.(8), demonstrated the interactions of one variable on the others.

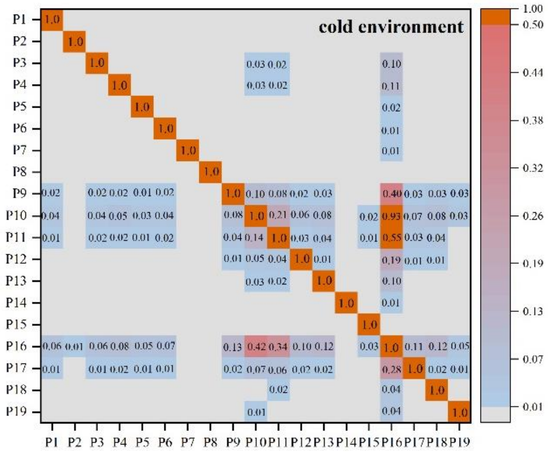
Fig. 6 demonstrated the interactive routes between the 19 variables under cold, neutral, and hot environments. All leading diagonal values in the matrix were close to 1.0, indicating that the trained interaction matrixes were stable and suitable for this research area. The coded values of the corresponding positions above and below the diagonal were different. The asymmetry of the matrixes also confirmed that there was a coupling relationship between the factors, not a simple linear relationship. The corresponding detailed code values in Fig. 6 are described in Appendix A.

It can be seen from Fig.6(a) that clothing insulation, metabolic rate, and outdoor environmental parameters strongly interact with the indoor air temperature in cold environments, with an interaction coefficient more significant than 0.3. As expected, this indicated that the indoor air temperature greatly affected indoor relative humidity and air velocity, and the interaction strength was more than 0.1. This was consistent with previous conclusions that the outdoor air temperature positively affected clothing insulation, as the interaction coefficient between outdoor air temperature and clothing insulation was 0.21 [46]. Various climate zones significantly affected indoor air temperature and the indoor air temperature varied greatly between climate zones in cold environments.

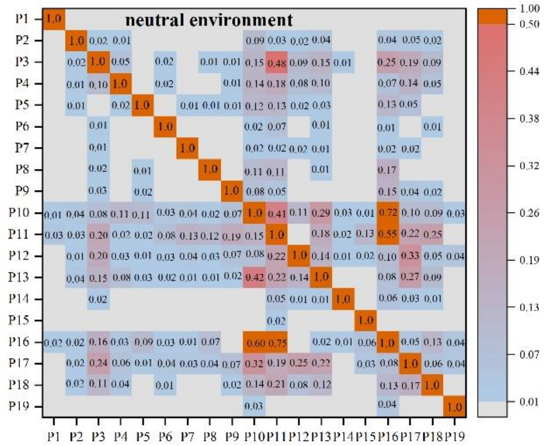
Fig.6(b) illustrated that neutral environments exhibited more complex interactions between factors than those in cold and hot environments. Interaction coefficients greater than 0.5 existed between clothing insulation, outdoor air temperature, and indoor air temperature. There was also a strong interaction between clothing insulation and outdoor relative humidity and outdoor air velocity.

Different BMIs also influenced the indoor environmental parameters in neutral environments, implying that occupants with different heights and weights preferred different environmental parameters. Furthermore, the effect of thermal experience on the clothing insulation was significant (0.11) and may be attributed to thermal adaptation. Similarly, the outdoor air temperature affected the window-opening and air conditioning behaviors, with an interaction coefficient exceeding 0.1.

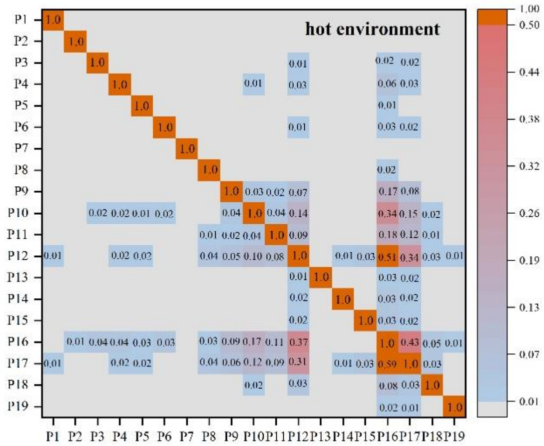
In hot environments, clothing insulation, metabolic rate, and outdoor environmental parameters strongly interacted with indoor environmental parameters. The outdoor relative humidity had a powerful impact on the indoor environmental parameters, with an interaction coefficient of 0.51. The outdoor air temperature also affected the outdoor relative humidity, which indicated that the outdoor air temperature and relative humidity played a significant role in occupants' thermal comfort and affected their ability to control the indoor air temperature in hot environments. The interaction coefficient between indoor air temperature and indoor relative humidity was 0.43. Indoor and outdoor environmental parameters varied with seasons and climate zones, and weather also significantly impacted clothing insulation and outdoor relative humidity.



(a) cold environment



(b) neutral environment



(c) hot environment

Fig.6. The interactive influence between the 19 variables under different environments.

(P_1, Gender; P_2, Age; P_3, BMI; P_4, Climate zone; P_5, Season; P_6, Weather; P_7, Construction age; P_8, Thermal experience; P_9, Metabolic rate; P_{10}, Clothing insulation; P_{11}, Outdoor air temperature; P_{12}, Outdoor relative humidity; P_{13}, Outdoor velocity; P_{14}, Window-opening behavior; P_{15}, Air-conditioning usage behavior; P_{16}, Indoor air temperature; P_{17}, Indoor relative humidity; P_{18}, Indoor velocity; P_{19}, Thermal expectation.)

4.2. The proposition of the path hypothesis and model structure

A conceptual framework with the directed connections for the path analysis model was proposed based on the thermal adaptation mechanism described in Fig.4 and the interaction pathways between latent variables and the influences from the observed variables. As shown in Fig.7, the established hypothesis framework contains 11 main hypotheses (H1 to H11) to reveal the relationships between subjective thermal perception and physical environmental, physiological, behavioral, and psychological factors. Subjective thermal perception incorporated two indicators: thermal sensation and thermal acceptability, to characterize an individual's evaluation of the indoor thermal environment.

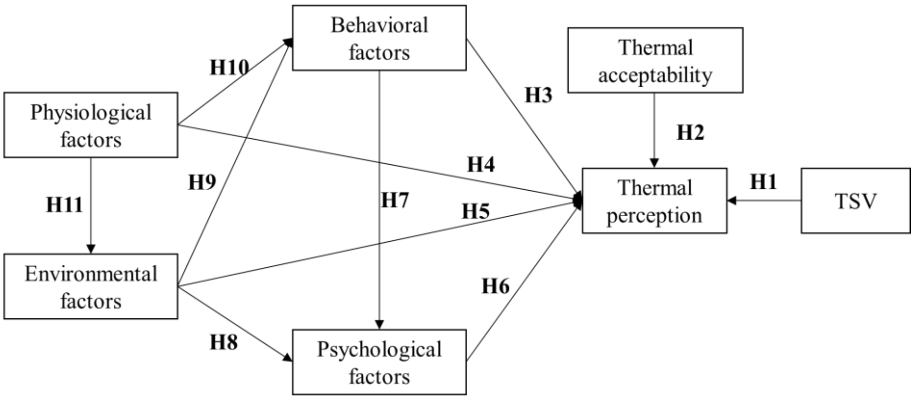


Fig.7. The proposed conceptual framework for the path analysis model.

4.3. The path analysis modeling results

After establishing the model assumptions, the Maximum Likelihood estimation method was used to estimate the direct and indirect relationships. Table 3 lists the results of various goodness-of-fit indices for the path analysis models under cold, neutral, and hot environments. The three models under different environments were shown to have a good fit based on the values of RMSEA, GFI, NFI, IFI, and CFI, which were greater than the empirical cut-off criterion given in Table 1. The reason for the values of χ^2/df being more than 3 was that the amount of data was extremely large, especially for the neutral environment. Overall, the structure of the direct and indirect relationships was proved to be significant.

Table 3. Results of various goodness-of-fit indices for the path analysis models for different environments.

Evaluation index	**Model parameters**		
	Cold environment	**Neutral environment**	**Hot environment**
χ^2/df	6.246	31.171	5.275
RMSEA	0.062	0.077	0.070
GFI	0.971	0.965	0.938
NFI	0.930	0.925	0.908
IFI	0.940	0.927	0.901
CFI	0.940	0.927	0.901

Figs. 8, 9, and 10 illustrate the estimates and significance levels in the path analysis models in the cold, neutral, and hot environments, respectively. Rectangular forms represent all observation variables with ovals expressing the latent variables in the figures. The coefficient 'r' characterizes the relationship of the connection paths. High coefficients indicate a solid relationship between the variables and the independent variables, and the low values suggest weak relationships. The positive coefficients indicated that the independent variables' value directly changed due to the values of the other variables. On the contrary, the negative coefficients suggested that the independent variable is inversely proportional to the other variables' value. The significance levels of the direct connections were also presented in the three figures (***: $p < 0.01$, **: $p < 0.05$ and *: $p < 0.1$).

As demonstrated in Fig.8, thermal sensation in the cold environment was directly affected by environmental factors (r=0.81), physiological factors (/), behavioral factors (r=0.36), and psychological factors (r=0.74). The effect of environmental factors arose from indoor air temperature (r=0.88), relative humidity (r=-0.25), indoor air velocity (r=-0.23), and season (r=-0.39). Together, the low air temperature, high relative humidity, and high air velocity exacerbate discomfort in a cold environment. The influence of physiological factors was achieved through gender (r=-0.46) and BMI (r=0.52). Females were more sensitive to the cold environment than males, and occupants with a lower BMI were more likely to feel cold than those with a high BMI. The effects of behavioral factors arose from adjusting the clothing insulation (r=0.87) and window-opening behavior (r=0.05). Even in a cold environment, opening windows voluntarily increases occupants' thermal comfort. Psychological factors influenced thermal perception through thermal expectation (r=0.73) and thermal experience (r=0.05).

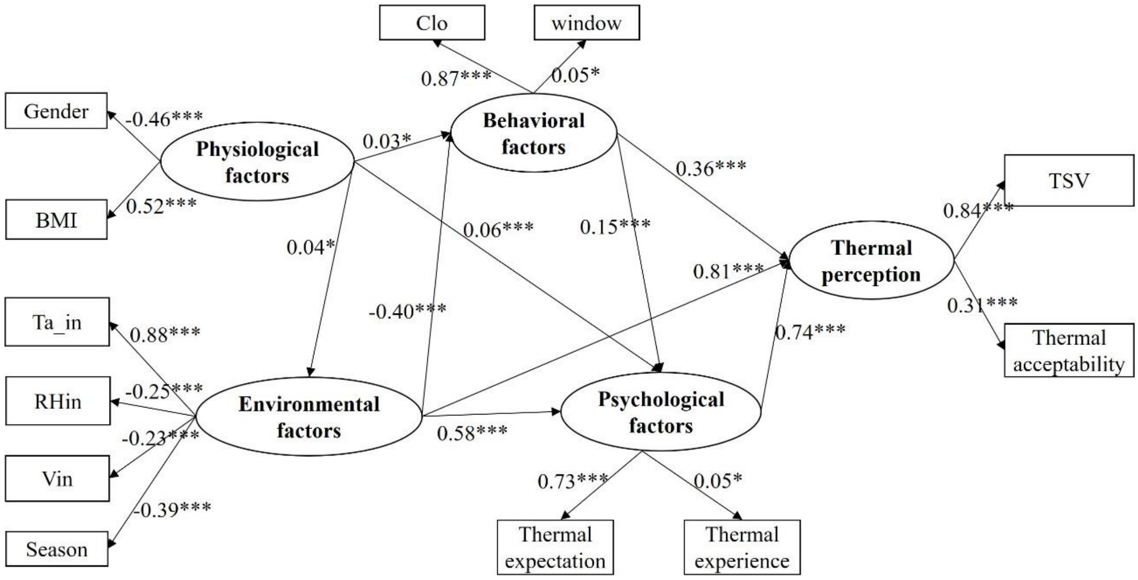


Fig.8. Estimates and significant levels in the path diagram of the model in a cold environment.

In neutral environments, as shown in Fig.9, environmental factors (r=0.66), behavioral factors (r=0.29), and psychological factors (r=0.89) exert a direct influence on thermal sensation. The effect of physiological factors was insignificant in neutral environments, indicating no difference in thermal perception among occupants of different genders, ages, and BMIs. Indoor air temperature (r=0.90), relative humidity (r=0.08), air velocity (r=-0.19) and season (r=-0.46) showed an indirect influence on thermal sensation. The effects of behavioral factors were characterized by adjusting clothing insulation (r=0.95), window-opening behavior (r=0.24), and air conditioning behavior (r=0.06). Psychological factors influenced thermal perception through thermal expectation (r=0.71) and thermal experience (r=-0.06).

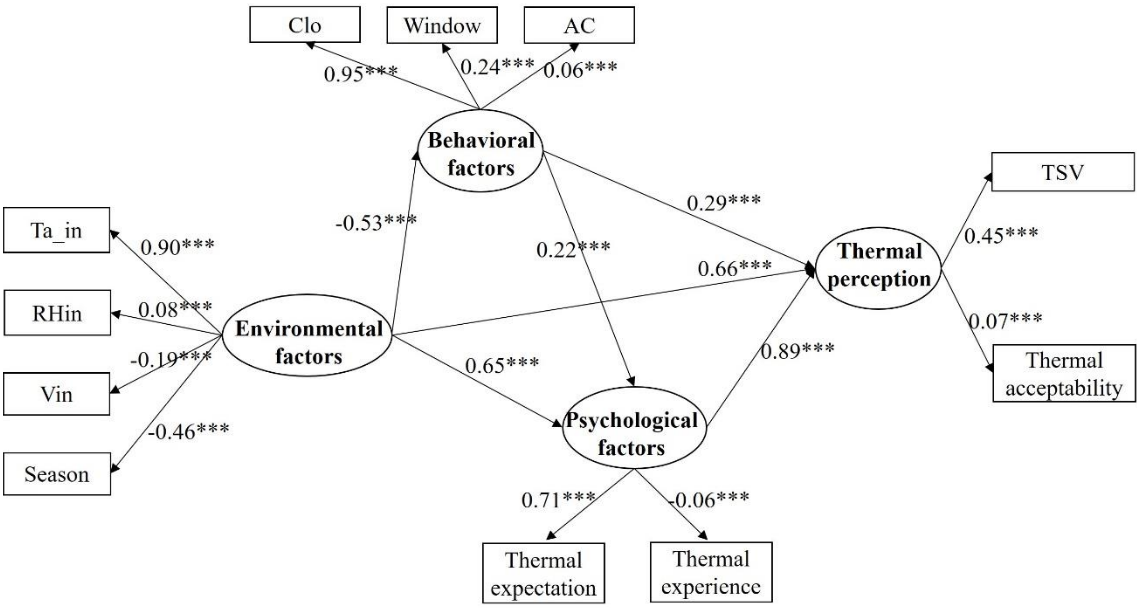


Fig.9. Estimates and significant levels in the path diagram of the model in a neutral environment.

It can be seen from Fig.10 that environmental factors (r=0.52), physiological factors (/), behavioral factors (r=0.42), and psychological factors (r=0.72) directly affect occupants' thermal sensation in a hot environment. Indoor air temperature, relative humidity, air velocity, and season had a positive influence on thermal sensation. The old people and females were more sensitive to perceiving the hot environment than their opposites, and occupants with higher BMIs were more likely to perceive warmth than those with lower BMIs.

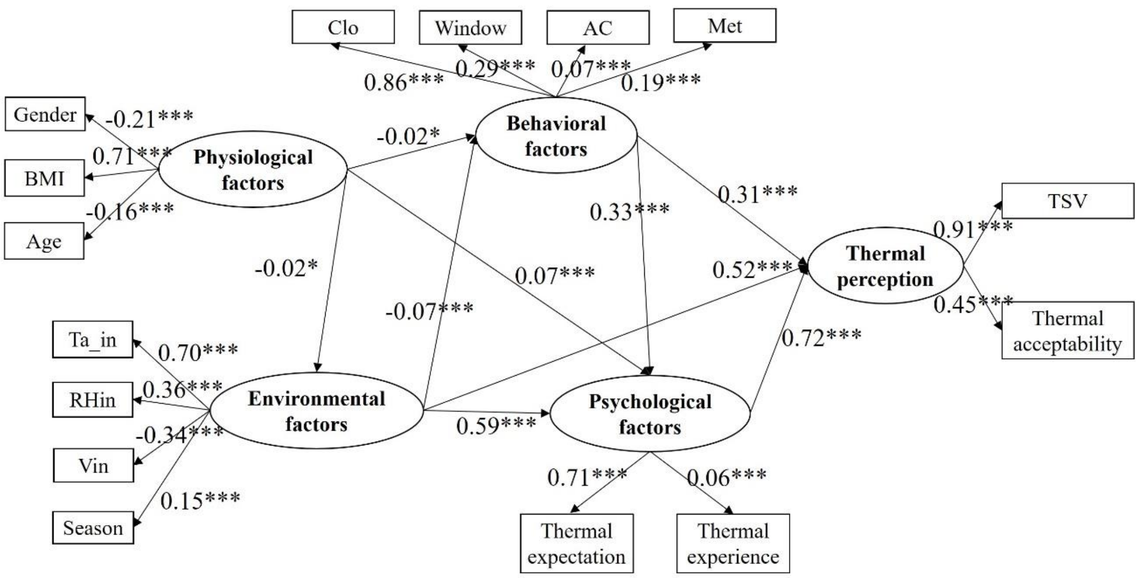


Fig.10. Estimates and significant levels in the path diagram of the model in a hot environment.

Table 4 demonstrates the direct, indirect, and total effects of individual factors on thermal sensation in the path models in different environments. It illustrates that psychological factors directly affect thermal sensation, while physiological factors indirectly influence thermal sensation. Environmental and behavioral factors had both direct and indirect effects on thermal sensation.

Among the four latent variables, it was determined that environmental factors had the most significant total effect on thermal sensation, followed by psychological factors, behavioral factors, and physiological factors in cold and hot environments. The physiological factors had no noteworthy impact on thermal sensation in the neutral environment, therefore, physiological factors and the related observed variables were not included in the model after verifying their relationships.

In terms of the observed variables, indoor air temperature had the most significant indirect and total effects in different environments, followed by the thermal expectation and the clothing adjustment behavior. Except for the negative effects of indoor relative humidity, indoor air velocity, season, and gender, other observed variables positively affected thermal sensation in a cold environment.

In the neutral environment, the effects of season and clothing adjustment behavior were similar, but the effects of the two on thermal sensation were in opposite directions. The impact of clothing adjustment behavior was positive, and the effect of season was negative. Except for the negative effects of indoor air velocity, season and thermal experience, other observed variables positively affected thermal sensation in the neutral environment.

In addition to indoor air temperature and thermal expectation, the clothing adjustment behavior, indoor relative humidity, air velocity, and window adjustment behavior significantly affected the thermal sensation in the hot environment. Except for the negative effects of indoor air velocity and gender, other observed variables had positive effects on thermal sensation in the hot environment.

Table 4. Direct, indirect and total effects of individual factors affecting thermal sensation in the path models in different indoor environments.

Description	**Cold environment**			**Neutral environment**			**Hot environment**		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Environmental parameters	0.68	0.20	0.88	0.30	0.14	0.44	0.47	0.35	0.82
Physiological	0.00	0.09	0.09	N/A	N/A	N/A	0.00	0.03	0.03

factors									
Behavioral factors	0.30	0.09	0.40	0.13	0.09	0.22	0.28	0.22	0.50
Psychological factors	0.62	0.00	0.62	0.40	0.00	0.40	0.66	0.00	0.66
Ta_in	0.00	0.78	0.78	0.00	0.40	0.40	0.00	0.58	0.58
RHin	0.00	-0.22	-0.22	0.00	0.04	0.04	0.00	0.30	0.30
Vin	0.00	-0.20	-0.20	0.00	-0.08	-0.08	0.00	-0.28	-0.28
Season	0.00	-0.34	-0.34	0.00	-0.20	-0.20	0.00	0.12	0.12
Gender	0.00	-0.04	-0.04	N/A	N/A	N/A	0.00	-0.01	-0.01
BMI	0.00	0.05	0.05	N/A	N/A	N/A	0.00	0.02	0.02
Age	N/A	N/A	N/A	N/A	N/A	N/A	0.00	0.00	0.00
Clothing behavior	0.00	0.34	0.34	0.00	0.21	0.21	0.00	0.43	0.43
Window behavior	0.00	0.02	0.02	0.00	0.05	0.05	0.00	0.14	0.14
Air conditioning behavior	N/A	N/A	N/A	0.00	0.01	0.01	0.00	0.03	0.03
Metabolic rate	N/A	N/A	N/A	N/A	N/A	N/A	0.00	0.09	0.09
Thermal expectation	0.00	0.45	0.45	0.00	0.28	0.28	0.00	0.47	0.47
Thermal experience	0.00	0.03	0.03	0.00	-0.02	-0.02	0.00	0.04	0.04

(Note, 'N/A' denotes that this factor is not involved in the model since its effect is not significant.)

5. Discussion

An essential target of adaptive thermal comfort research is to gain knowledge of the weight of the contribution of each factor to thermal comfort. Existing studies on human thermal comfort primarily focused on the effect of a single component keeping the others constant and statistically describing the independence of state variables. However, any change in occupants' thermal comfort results from the comprehensive and interactive influences of all the variables.

This study investigated the driving effect of different variables on human thermal comfort by the interactive influences of the variables. Air temperature, relative humidity, and air velocity are generally recognized as the most critical parameter in most thermal comfort studies [11, 47]. Our results supported this finding by weighting these environmental factors, in other words, indoor air temperature exhibited the most significant indirect and total effects among the studied explanatory variables in different environments.

As a psychological factor, thermal expectation was also into a force to be reckoned with because of the prominent indirect and total effects in cold, neutral, and hot environments. In the ePMV model, the critical tweak was declaring the impact of thermal expectation on thermal judgment, which confirmed that thermal expectation was crucial [13]. Even so, it is worth noting that concepts related to psychological adaptation remain vague in contrast to physiological and behavioral adaptation. In this study, the thermal expectation was utilized as a mediator linking other adaptive pathways with thermal perception, where physiological and behavioral adaptation ultimately act on thermal perception by psychological adaptation.

The adjustment of clothing insulation is a powerful method, and the importance of clothing insulation for thermal comfort has been confirmed by many studies [6, 48-50]. After ranking indoor air temperature, thermal expectation, and clothing insulation, the season made an outstanding contribution to influencing thermal comfort, which reported very similar findings in [46]. Few studies focused on the Body Mass Index (BMI) and we found that the influence of BMI was at a moderate level among the 19 parameters, which was similar to the results in [20].

It is worth noting that, as one of the six input parameters of the PMV model, the contribution of metabolic rate is surprisingly minimal. One important reason may be that only four discrete categories in the questionnaires were used to reflect the differences in metabolic rate due to the estimation and measurement difficulties, indicating that we might need to clarify the variations of metabolic rate and refine the classification. We place hopes that applying wearable sensors will provide continuous feedback enabling the determination of the actual metabolic rate value [47, 51].

Some variables played marginal roles in determining occupants' thermal comfort. The previous studies [52, 53] supported the statement that gender has no significant impact on occupants' thermal comfort. But some controversial voices are giving contradictory results by reporting that females are more sensitive to thermal conditions than males [54]. In this study, we conclude that gender significantly affected human thermal perception in cold conditions while having no substantial impact in neutral and hot environments. Our study also confirmed the diversity of thermal adaptation mechanisms in various thermal conditions. In cold and hot environments, a significant impact of indoor air temperature was evident and stood out among the other parameters. In comparison, the influence of explanatory variables on thermal perception was more dispersed in a neutral environment than in cold and hot environments. It indicated that it is more capable of mobilizing the thermal adaptive capacity in neutral environments, whereas the effects of environmental parameters overshadow the influence of adaptive pathways in an extreme environment.

Nonetheless, several uncertainties worthy of further discussion still remain. Firstly, some physiological factors, including skin temperature and heart rate, have not been included in the path models because of the practical difficulties in their measurement, which may account for the small effect of physiological factors on thermal perception. More physiological factors should be surveyed in further research to describe and summarize the overall findings. Secondly, further studies should include a broader range of surveys to examine the thermal adaptation of specific groups, including the elderly and vulnerable.

6. Conclusions

This study proposes an Interaction Matrix-based Path Analysis (IMPA) modeling framework to obtain a comprehensive understanding of the correlativity and causality among the explanatory variables and thermal comfort. The interaction matrix between explanatory variables was first conducted to describe the interactive pathways and path analysis models that were employed to identify the contribution of each variable to thermal sensation. A field investigation of a broader range of variables, spanning the five climate zones of China, was carried out to verify this approach. The advantage of this framework is its ability to clearly describe the interactive pathways and comprehensively examine the causal relationships. The key findings can be summarized as follows:

(1) Eleven main hypotheses were proposed based on thermal adaptation theory and the interaction pathways between latent and observed variables. The hypotheses with the directed connections revealed the relationships between subjective thermal perception and physical environmental, physiological, behavioral, and psychological factors. Using the path analysis models, the hypothetical causalities between explanatory variables and thermal sensation were verified, and the effects of individual adaptive principles on thermal perception distinguished.

(2) Variations in interactive pathways and driving effects result from different environmental conditions. In cold and hot environments, environmental factors have the most significant total effects on thermal sensation, followed by psychological, behavioral, and physiological factors. In neutral environments, environmental factors are dominant and physiological factors (gender, age,

and BMI) have no substantial impact on thermal sensation. It confirmed the diversity of thermal adaptation mechanisms in various thermal conditions. It inferred that improving the psychological demands is critical for guaranteeing thermal comfort in the absence of positive environmental changes.

(3) Explanatory variables affect thermal perception via various routes, resulting in different effects. Indoor air temperature has the most significant total effects in different environments, followed by thermal expectation and clothing insulation behavior. In general, the impact of air temperature doubly outweighs the effects of thermal expectation. The total effects of the season are revealed to be significant in cold and neutral environments, while it is deemed negligible in hot environments. In contrast with the effects in neutral environments, indoor relative humidity and air velocity are revealed to affect thermal sensation significantly in cold and hot environments.

This study has provided an innovative way to examine the associations between explanatory variables and thermal comfort as well as the causal relationships that underpin them. It offers a “transparent” explanation to describe the direct and indirect influence pathways of thermal comfort, which might help to open up new possibilities for revealing the thermal adaptation processes.

Acknowledgements

This work was supported by the National Key R&D Program of China [Grant No: 2022YFC3801504], the Natural Science Foundation of Chongqing, China [Grant No: cstc2021ycjh-bgzxm0156] and the International Collaboration project [Grant No: B13041]. Ru Ming would like to thank the Chinese Scholarship Council [No: 201906050234] for their sponsorship of a research visit to study at Aalto University in Finland.

Appendix A. The corresponding encoding of the interaction matrix under different environments in Fig.6.

A.1. The encoding of the interaction matrix for describing the pathways under a cold environment (Fig.6(a)).

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	**Cause (C)**
P_1	**1.00E+00**	6.97E-05	3.08E-04	1.02E-04	1.37E-03	1.74E-05	6.55E-04	6.79E-05	3.56E-04	4.79E-04	1.96E-04	4.45E-04	7.17E-04	3.30E-05	4.08E-04	5.65E-03	1.85E-04	5.41E-06	4.02E-04	**1.15E-02**
P_2	1.66E-04	**1.00E+00**	2.08E-04	1.84E-04	8.39E-05	1.73E-04	7.57E-04	4.43E-04	3.72E-04	1.74E-03	4.67E-04	9.25E-05	1.23E-03	9.18E-04	5.62E-04	4.33E-03	5.73E-04	3.87E-04	7.36E-05	**1.28E-02**
P_3	1.22E-03	5.21E-04	**1.00E+00**	2.58E-03	1.17E-03	3.96E-03	9.52E-04	5.23E-04	6.54E-03	2.60E-02	1.96E-02	4.15E-03	7.83E-03	1.76E-03	2.46E-03	1.01E-01	6.31E-03	7.05E-03	1.33E-03	**1.95E-01**
P_4	2.32E-03	3.13E-04	3.70E-03	**1.00E+00**	2.61E-03	3.85E-03	3.91E-04	5.67E-04	7.77E-03	2.68E-02	2.08E-02	5.06E-03	7.50E-03	6.35E-04	2.33E-03	1.06E-01	6.68E-03	7.03E-03	1.40E-03	**2.06E-01**
P_5	1.47E-04	1.22E-04	6.63E-04	2.73E-04	**1.00E+00**	8.97E-04	1.68E-04	6.92E-05	1.53E-03	5.72E-03	3.25E-03	5.86E-04	1.33E-03	6.59E-04	4.12E-04	2.15E-02	1.34E-03	9.49E-04	1.88E-04	**3.98E-02**
P_6	1.37E-03	6.51E-04	4.29E-04	1.62E-03	9.05E-04	**1.00E+00**	1.33E-03	7.48E-04	1.84E-03	2.34E-03	2.47E-03	1.06E-03	1.24E-04	1.63E-03	4.39E-04	1.18E-02	5.50E-04	8.32E-04	6.69E-04	**3.08E-02**
P_7	2.38E-04	2.26E-04	5.94E-04	1.82E-04	4.29E-04	2.28E-04	**1.00E+00**	2.32E-04	7.55E-04	3.93E-03	1.44E-03	1.89E-04	1.36E-03	7.26E-04	3.47E-04	1.34E-02	8.66E-04	2.33E-04	4.72E-06	**2.54E-02**
P_8	3.32E-04	1.23E-04	4.88E-04	1.25E-04	2.68E-04	1.41E-04	1.27E-03	**1.00E+00**	6.63E-04	7.16E-04	1.03E-03	2.79E-04	1.82E-03	8.75E-04	1.56E-04	2.20E-03	4.91E-04	9.86E-04	8.43E-04	**1.28E-02**
P_9	1.53E	3.55E	1.53E	2.08E	1.41E	1.76E	1.91E	1.22E	**1.00E**	1.01E	8.27E	2.45E	2.98E	2.60E	8.00E	3.98E	2.62E	3.06E	1.24E	**8.06E**

	-02	-03	-02	-02	-02	-02	-03	-03	**+00**	-01	-02	-02	-02	-03	-03	-01	-02	-02	-02	**-01**
PP_{10}	3.80E-02	9.42E-03	3.96E-02	5.22E-02	3.29E-02	4.48E-02	3.62E-03	2.27E-03	8.32E-02	**1.00E+00**	2.12E-01	6.24E-02	7.74E-02	5.99E-03	2.13E-02	1.04E+00	6.76E-02	7.69E-02	3.07E-02	**1.90E+00**
P_{11}	1.09E-02	3.18E-03	2.06E-02	2.01E-02	1.30E-02	2.03E-02	1.82E-03	2.11E-03	4.02E-02	1.40E-01	**1.00E+00**	2.72E-02	3.95E-02	3.61E-03	1.18E-02	5.52E-01	3.48E-02	3.65E-02	9.01E-03	**9.87E-01**
P_{12}	6.96E-03	1.70E-03	7.32E-03	9.14E-03	6.14E-03	8.92E-03	1.70E-04	4.27E-04	1.47E-02	4.77E-02	3.90E-02	**1.00E+00**	1.46E-02	2.51E-04	4.03E-03	1.89E-01	1.26E-02	1.36E-02	6.93E-03	**3.83E-01**
P_{13}	2.18E-03	7.29E-04	3.72E-03	3.91E-03	2.78E-03	3.00E-03	7.24E-04	8.14E-05	7.42E-03	2.58E-02	1.73E-02	4.76E-03	**1.00E+00**	6.89E-04	2.10E-03	1.00E-01	6.15E-03	5.92E-03	1.36E-03	**1.89E-01**
P_{14}	9.14E-04	4.50E-04	4.16E-04	1.25E-03	1.17E-03	2.62E-04	5.73E-04	6.78E-04	1.98E-03	3.44E-03	1.90E-03	1.15E-03	4.38E-04	**1.00E+00**	6.96E-05	1.40E-02	8.95E-04	5.78E-04	3.89E-04	**3.06E-02**
P_{15}	1.33E-03	3.37E-04	1.99E-04	7.29E-04	1.25E-04	2.19E-04	9.22E-05	5.45E-04	4.94E-04	2.51E-03	1.25E-03	6.81E-04	7.79E-04	1.25E-05	**1.00E+00**	7.32E-03	6.81E-04	3.86E-04	4.35E-04	**1.81E-02**
P_{16}	5.81E-02	1.42E-02	6.27E-02	8.03E-02	5.12E-02	6.99E-02	4.61E-03	4.17E-03	1.31E-01	4.18E-01	3.35E-01	9.66E-02	1.22E-01	7.33E-03	3.37E-02	**1.00E+00**	1.07E-01	1.22E-01	4.70E-02	**1.76E+00**
P_{17}	1.34E-02	2.90E-03	1.04E-02	1.65E-02	1.04E-02	1.40E-02	2.36E-03	8.33E-04	2.34E-02	6.96E-02	6.03E-02	1.83E-02	2.04E-02	3.60E-03	5.92E-03	2.75E-01	**1.00E+00**	2.19E-02	1.14E-02	**5.81E-01**
P_{18}	8.87E-03	1.75E-03	2.26E-03	6.53E-03	4.70E-03	7.55E-03	3.74E-03	9.59E-04	6.24E-03	7.95E-03	2.13E-02	6.12E-03	6.25E-03	4.72E-03	1.89E-03	3.86E-02	4.21E-03	**1.00E+00**	8.24E-03	**1.42E-01**
P_{19}	1.82E-03	8.59E-04	1.78E-03	2.52E-03	2.20E-03	1.90E-03	1.20E-03	5.02E-04	4.30E-03	1.08E-02	7.70E-03	2.55E-03	2.09E-03	5.41E-04	3.67E-04	4.35E-02	2.78E-03	2.60E-03	**1.00E+00**	**9.00E-02**
Effect	**1.64E-01**	**4.11E-02**	**1.71E-01**	**2.19E-01**	**1.45E-01**	**1.98E-01**	**2.63E-02**	**1.64E-02**	**3.33E-01**	**8.94E-01**	**8.28E-01**	**2.56E-01**	**3.36E-01**	**3.66E-02**	**9.63E-02**	**2.92E+00**	**2.80E-01**	**3.28E-01**	**1.33E-01**	

(E)

A.2. The encoding of the interaction matrix for describing the pathways under a neutral environment (Fig.6(b)).

	***P*₁**	***P*₂**	***P*₃**	***P*₄**	***P*₅**	***P*₆**	***P*₇**	***P*₈**	***P*₉**	***P*₁₀**	***P*₁₁**	***P*₁₂**	***P*₁₃**	***P*₁₄**	***P*₁₅**	***P*₁₆**	***P*₁₇**	***P*₁₈**	***P*₁₉**	**Cause (C)**
***P*₁**	**1.00E+00**	5.67E-05	2.62E-05	3.93E-04	3.99E-05	4.59E-05	1.17E-04	4.36E-04	7.17E-04	1.09E-03	7.16E-04	2.76E-03	1.89E-05	8.05E-05	7.57E-04	3.68E-03	3.34E-03	5.05E-04	9.47E-05	**1.49E-02**
***P*₂**	2.73E-04	**1.00E+00**	1.69E-04	1.57E-04	3.45E-04	1.90E-04	9.93E-05	6.92E-05	2.45E-04	3.42E-06	3.90E-04	1.14E-03	4.58E-05	7.14E-05	2.03E-04	4.41E-05	5.19E-04	5.75E-04	2.08E-04	**4.75E-03**
***P*₃**	9.97E-04	5.68E-04	**1.00E+00**	8.79E-04	5.38E-04	8.16E-04	5.95E-05	3.06E-03	2.26E-03	3.45E-03	4.03E-03	1.37E-02	2.03E-04	8.43E-04	3.35E-03	1.85E-02	1.78E-02	1.64E-03	1.59E-03	**7.42E-02**
***P*₄**	9.44E-04	4.59E-04	1.36E-03	**1.00E+00**	1.83E-03	1.59E-03	2.98E-04	2.68E-03	5.97E-03	1.09E-02	7.96E-03	2.54E-02	5.01E-05	1.31E-03	1.02E-03	5.53E-02	3.00E-02	3.42E-03	2.98E-04	**1.51E-01**
***P*₅**	1.04E-04	2.25E-04	1.30E-04	6.84E-04	**1.00E+00**	2.88E-04	1.81E-04	4.86E-04	1.31E-03	2.28E-03	1.51E-03	4.50E-03	4.16E-05	3.53E-04	6.07E-04	1.00E-02	4.99E-03	8.45E-04	3.14E-05	**2.86E-02**
***P*₆**	4.58E-04	3.06E-04	2.83E-04	1.08E-03	2.17E-05	**1.00E+00**	2.85E-04	1.74E-03	3.02E-03	6.44E-03	4.48E-03	1.40E-02	5.64E-05	1.03E-03	2.03E-03	3.01E-02	1.80E-02	1.53E-03	5.23E-04	**8.54E-02**
***P*₇**	1.97E-04	5.21E-04	1.02E-03	5.73E-04	6.53E-04	4.88E-04	**1.00E+00**	6.97E-05	1.08E-03	1.94E-03	9.83E-04	3.47E-03	2.78E-05	2.12E-04	3.40E-04	9.79E-03	3.40E-03	3.72E-04	4.03E-04	**2.56E-02**
***P*₈**	1.76E-04	4.47E-04	1.18E-03	8.29E-04	1.04E-03	5.55E-04	2.14E-05	**1.00E+00**	2.17E-03	3.58E-03	2.37E-03	8.71E-03	3.72E-05	1.73E-04	4.73E-05	1.90E-02	9.10E-03	8.11E-04	3.70E-04	**5.06E-02**
***P*₉**	9.79	2.84	7.27	7.68	5.62	6.31	1.26	4.89	**1.00**	3.28	2.17	7.16	1.95	1.78	7.65	1.65	8.19	9.23	2.71	**4.25**

	E-04	E-03	E-03	E-03	E-03	E-03	E-03	E-03	**E+00**	E-02	E-02	E-02	E-04	E-03	E-04	E-01	E-02	E-03	E-03	**E-01**
***P*₁₀**	5.21E-04	7.42E-03	2.00E-02	1.53E-02	1.09E-02	1.57E-02	2.78E-03	4.91E-03	3.65E-02	**1.00E+00**	4.13E-02	1.35E-01	2.86E-05	2.16E-03	4.86E-03	3.40E-01	1.50E-01	1.62E-02	8.48E-03	**8.12E-01**
***P*₁₁**	3.78E-03	5.40E-05	5.89E-04	7.64E-03	5.88E-03	2.88E-03	6.45E-04	1.26E-02	2.00E-02	3.74E-02	**1.00E+00**	9.36E-02	2.42E-04	4.22E-03	9.45E-03	1.78E-01	1.16E-01	1.22E-02	1.76E-03	**5.06E-01**
***P*₁₂**	1.07E-02	2.95E-03	3.45E-03	2.09E-02	1.64E-02	3.89E-03	9.53E-04	3.84E-02	5.46E-02	1.04E-01	7.94E-02	**1.00E+00**	6.60E-04	1.14E-02	3.28E-02	5.08E-01	3.35E-01	2.98E-02	1.07E-02	**1.26E+00**
***P*₁₃**	6.33E-04	1.30E-04	7.17E-07	1.08E-03	7.56E-04	6.44E-04	1.39E-05	1.93E-03	3.41E-03	6.48E-03	4.69E-03	1.49E-02	**1.00E+00**	9.16E-04	1.25E-03	3.01E-02	1.88E-02	1.92E-03	2.15E-04	**8.79E-02**
***P*₁₄**	7.83E-04	6.10E-04	1.61E-04	1.05E-03	2.69E-04	4.22E-04	2.67E-04	2.14E-03	3.05E-03	6.90E-03	5.03E-03	1.61E-02	1.15E-04	**1.00E+00**	1.75E-03	3.46E-02	2.07E-02	1.46E-03	8.00E-04	**9.61E-02**
***P*₁₅**	1.13E-03	2.40E-04	4.82E-04	1.30E-03	2.05E-03	1.91E-04	1.83E-04	2.28E-03	3.28E-03	6.32E-03	5.22E-03	1.84E-02	1.29E-04	4.36E-04	**1.00E+00**	3.49E-02	2.15E-02	1.72E-03	6.40E-04	**1.00E-01**
***P*₁₆**	6.01E-03	1.36E-02	3.55E-02	3.82E-02	2.83E-02	3.14E-02	5.79E-03	2.63E-02	9.26E-02	1.69E-01	1.12E-01	3.71E-01	7.31E-04	9.71E-03	5.37E-03	**1.00E+00**	4.27E-01	4.59E-02	1.23E-02	**1.43E+00**
***P*₁₇**	1.14E-02	1.91E-03	1.81E-04	2.46E-02	1.91E-02	6.89E-03	1.58E-03	4.10E-02	6.34E-02	1.21E-01	9.05E-02	3.08E-01	6.80E-04	1.20E-02	3.35E-02	5.95E-01	**1.00E+00**	3.41E-02	9.41E-03	**1.37E+00**
***P*₁₈**	5.61E-04	2.00E-03	5.73E-03	4.33E-03	3.76E-03	4.27E-03	9.14E-04	7.23E-04	8.64E-03	1.53E-02	9.84E-03	3.28E-02	6.52E-04	1.06E-03	2.12E-03	8.33E-02	3.40E-02	**1.00E+00**	2.79E-03	**2.13E-01**
***P*₁₉**	3.01E-04	1.33E-04	2.75E-04	7.24E-04	5.58E-04	3.06E-04	4.89E-05	1.02E-03	2.00E-03	3.74E-03	2.46E-03	9.18E-03	1.84E-04	2.96E-04	8.72E-04	1.94E-02	1.07E-02	9.55E-04	**1.00E+00**	**5.32E-02**
Effect	**3.99E-02**	**3.44E-02**	**7.78E-02**	**1.27E-01**	**9.80E-02**	**7.69E-02**	**1.55E-02**	**1.45E-01**	**3.04E-01**	**5.32E-01**	**3.94E-01**	**1.14E+00**	**4.10E-03**	**4.81E-02**	**1.01E-01**	**2.13E+00**	**1.30E+00**	**1.63E-01**	**5.33E-02**	

(E)

A.3. The encoding of the interaction matrix for describing the pathways under a hot environment (Fig.6(c)).

	***P*₁**	***P*₂**	***P*₃**	***P*₄**	***P*₅**	***P*₆**	***P*₇**	***P*₈**	***P*₉**	***P*₁₀**	***P*₁₁**	***P*₁₂**	***P*₁₃**	***P*₁₄**	***P*₁₅**	***P*₁₆**	***P*₁₇**	***P*₁₈**	***P*₁₉**	**Cause (C)**
***P*₁**	**1.00E+00**	8.94E-05	4.15E-04	8.51E-04	1.88E-04	**1.73E-04**	2.91E-04	6.39E-06	1.20E-03	1.11E-03	5.05E-03	5.86E-04	8.91E-04	7.75E-04	1.53E-03	1.32E-04	1.20E-03	7.52E-04	1.15E-04	·
***P*₂**	2.82E-03	**1.00E+00**	1.90E-02	1.51E-02	7.15E-03	3.46E-03	6.97E-04	3.65E-03	1.01E-03	9.35E-02	3.03E-02	2.24E-02	4.16E-02	3.64E-03	7.87E-04	4.18E-02	4.76E-02	1.65E-02	1.32E-03	**3.52E-01**
***P*₃**	5.91E-04	1.60E-02	**1.00E+00**	5.23E-02	1.11E-03	2.28E-02	5.23E-03	1.12E-02	1.37E-02	1.48E-01	4.88E-01	9.53E-02	1.52E-01	1.34E-02	2.71E-04	2.48E-01	1.89E-01	9.52E-02	8.39E-03	**1.56E+00**
***P*₄**	1.10E-03	1.05E-02	1.01E-01	**1.00E+00**	4.08E-03	1.76E-02	1.91E-03	5.29E-05	1.09E-02	1.35E-01	1.77E-01	7.89E-02	1.05E-01	2.61E-03	9.35E-04	6.60E-02	1.38E-01	5.44E-02	9.06E-03	**9.14E-01**
***P*₅**	6.18E-03	1.14E-02	3.21E-03	1.73E-02	**1.00E+00**	2.73E-03	1.22E-02	1.42E-02	1.16E-02	1.17E-01	1.26E-01	2.25E-02	2.95E-02	1.22E-03	7.92E-03	1.26E-01	5.32E-02	3.10E-03	1.43E-03	**5.66E-01**
***P*₆**	1.25E-03	3.41E-05	1.13E-02	3.50E-03	1.63E-03	**1.00E+00**	4.42E-03	3.78E-03	7.64E-03	2.34E-02	6.93E-02	4.02E-03	1.32E-02	8.44E-04	4.86E-03	1.39E-02	3.69E-04	1.23E-02	6.86E-04	**1.76E-01**
***P*₇**	1.01E-03	8.68E-05	1.33E-02	1.60E-03	2.03E-03	3.02E-03	**1.00E+00**	3.33E-03	3.91E-03	2.00E-02	2.21E-02	1.64E-02	1.24E-02	1.85E-04	2.37E-03	2.23E-02	1.98E-02	1.48E-03	2.29E-03	**1.48E-01**
***P*₈**	4.98E-03	5.93E-03	2.39E-02	5.96E-03	1.46E-02	2.23E-03	1.40E-04	**1.00E+00**	7.50E-03	1.09E-01	1.15E-01	1.51E-04	1.36E-02	8.42E-04	3.78E-04	1.71E-01	2.29E-03	5.32E-03	6.03E-03	**4.89E-01**
***P*₉**	1.65E	1.09E	2.84E	4.55E	1.55E	1.85E	6.31E	5.18E	**1.00E**	7.50E	4.92E	9.35E	3.00E	3.74E	2.50E	1.47E	3.77E	1.65E	6.49E	**4.11E**

	-03	-03	-02	-05	-02	-03	-03	-03	**+00**	-02	-02	-03	-03	-03	-03	-01	-02	-02	-03	**-01**
P_{10}	1.37E-02	4.00E-02	8.31E-02	1.15E-01	1.11E-01	3.04E-02	3.57E-02	1.88E-02	6.98E-02	**1.00E+00**	4.06E-01	1.15E-01	2.93E-01	2.73E-02	1.23E-02	7.24E-01	9.80E-02	9.38E-02	2.95E-02	**2.32E+00**
P_{11}	3.28E-02	2.76E-02	2.02E-01	2.03E-02	2.19E-02	7.64E-02	1.35E-01	1.17E-01	1.89E-01	1.52E-01	**1.00E+00**	5.09E-03	1.78E-01	2.09E-02	1.30E-01	5.53E-01	2.16E-01	2.47E-01	1.25E-03	**2.32E+00**
P_{12}	7.34E-03	1.13E-02	1.92E-01	2.96E-02	1.33E-02	3.01E-02	3.59E-02	2.66E-02	6.96E-02	8.06E-02	2.20E-01	**1.00E+00**	1.37E-01	1.38E-02	2.28E-02	1.02E-01	3.32E-01	4.70E-02	3.66E-02	**1.41E+00**
P_{13}	7.96E-03	3.52E-02	1.52E-01	8.07E-02	2.50E-02	2.25E-02	1.21E-02	1.44E-02	1.66E-02	4.24E-01	2.22E-01	1.38E-01	**1.00E+00**	6.46E-03	5.69E-03	7.75E-02	2.65E-01	9.38E-02	5.22E-03	**1.60E+00**
P_{14}	1.01E-03	1.38E-03	2.08E-02	3.46E-03	4.44E-03	2.17E-03	1.13E-03	2.32E-03	3.58E-03	9.71E-03	5.53E-02	1.15E-02	1.30E-02	**1.00E+00**	1.32E-03	6.26E-02	2.64E-02	1.31E-02	2.46E-03	**2.36E-01**
P_{15}	1.73E-04	1.92E-04	1.72E-03	6.31E-04	2.04E-04	1.01E-04	1.29E-03	1.94E-03	2.79E-03	3.49E-03	2.03E-02	3.95E-03	1.62E-03	5.10E-04	**1.00E+00**	9.11E-03	7.16E-03	1.64E-03	6.74E-04	**5.75E-02**
P_{16}	2.21E-02	1.72E-02	1.64E-01	3.11E-02	9.41E-02	2.52E-02	1.18E-02	7.21E-02	9.07E-03	6.05E-01	7.46E-01	4.77E-03	2.16E-02	1.75E-02	5.72E-02	**1.00E+00**	4.56E-02	1.32E-01	3.80E-02	**2.11E+00**
P_{17}	5.76E-03	1.99E-02	2.41E-01	5.92E-02	1.32E-02	4.16E-02	3.35E-02	3.90E-02	7.35E-02	3.17E-01	1.92E-01	2.55E-01	2.25E-01	8.54E-03	3.24E-02	7.60E-02	**1.00E+00**	6.36E-02	3.65E-02	**1.73E+00**
P_{18}	2.55E-03	1.93E-02	1.13E-01	4.25E-02	1.52E-03	1.50E-02	9.21E-03	4.39E-04	1.76E-02	1.37E-01	2.13E-01	8.05E-02	1.16E-01	4.75E-04	4.26E-04	1.25E-01	1.70E-01	**1.00E+00**	9.77E-03	**1.07E+00**
P_{19}	6.75E-04	4.78E-04	1.79E-03	2.67E-03	3.76E-03	5.52E-05	7.38E-05	2.35E-03	2.01E-03	2.95E-02	8.08E-03	4.03E-03	6.82E-03	1.96E-03	2.90E-03	3.81E-02	4.38E-03	3.62E-03	**1.00E+00**	**1.13E-01**
Effect	**1.14E-01**	**2.18E-01**	**1.37E+00**	**4.82E-01**	**3.35E-01**	**2.97E-01**	**3.07E-01**	**3.36E-01**	**5.11E-01**	**2.48E+00**	**3.16E+00**	**8.67E-01**	**1.36E+00**	**1.25E-01**	**2.87E-01**	**2.60E+00**	**1.65E+00**	**9.01E-01**	**1.96E-01**	

(E)

(P_1, Gender; P_2, Age; P_3, BMI; P_4, Climate zone; P_5, Season; P_6, Weather; P_7, Construction age; P_8, Thermal experience; P_9, Metabolic rate; P_{10}, Clothing insulation; P_{11}, Outdoor air temperature; P_{12}, Outdoor relative humidity; P_{13}, Outdoor velocity; P_{14}, Window-opening behavior; P_{15}, Air-conditioning usage behavior; P_{16}, Indoor air temperature; P_{17}, Indoor relative humidity; P_{18}, Indoor velocity; P_{19}, Thermal expectation.)

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