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A review of thermal comfort modeling of elderly people

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Abstract. With the global warming and aging of society, the analysis of thermal comfort of elderly people is becoming more important. One example is during heat wave period, the elderly are exposed to a hot environment for a long time, the probability of health problems (cardiovascular disease, mental confusion, etc.) may increase, and even death may occur. The thermal comfort model can predict the human thermal response and evaluate the ambient thermal environment. Therefore, thermal comfort models have a significant effect to improve the thermal sensation of occupants in a built environment. But models being established with adults' data may not be accurate enough in predicting the thermal response of the elderly. This paper reviews the existing thermal comfort models for the elderly and summarizes different types of thermal comfort models, including the thermoregulatory model, the thermal comfort model, and the machine learning model. The differences and the applicable conditions of models are summarized. This paper provides evidence from literature for the difference in thermal response between the elderly and young people, and also provides a reference for the establishment of a thermal comfort model for the elderly in the future.

Keywords. thermal comfort model, elderly people, human thermoregulation.
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1. Introduction

The impact of climate change on human body has been concerned [1], including mortality and morbidity caused by hot weather. More scholars began to focus on heat-related vulnerability and conducted researches [2]. According to the published literatures from different countries, it is found that the mortality of the elderly account for a high proportion [3,4]. Two issues can be extracted from these data: global aging and warming.

On the one hand, the global ageing society is accelerated growth [5,6]. Ageing means the functional decline of body organs and systems, suffering from various chronic diseases [7]. In terms of heat-related health, this degradation is mainly manifested in a preference for a warm environment and a reduced thermoregulatory response, which means less sensitive to changes in ambient thermal conditions. There may even be dangerous situations in which an appropriate response cannot be made to maintain the core temperature under some extreme weather [8,9]. Generally accepted reasons include: 1) Changes in body composition; 2) Lower metabolic rate; and 3) Decreased cardiovascular function [10]. On the other hand, global warming makes heat waves and extreme weather more frequent [11]. Some scholars have predicted the future heat-related mortality through modeling, and believe that the mortality will increase [12,13], while population aging will amplify this situation [3].

Facing the above problems, it is possible to alter the elderly's living environment to fulfill their comfort and health requirements, thereby reducing the threat of hot weather. The use of thermal comfort models can achieve the purpose of predicting the thermal response of the elderly. At present, scholars divide thermal comfort models into human thermoregulatory model, adaptive model and the latest machine learning model [14-16]. This paper mainly summarizes thermoregulatory models and adaptive models. However, most of the existing human thermal comfort models are established using the data of average adults (age between), which can not predict older people's response accuratly enough. Therefore, the human thermal comfort model of older people should be established specialy [10].

This paper reviews and summarizes the existing thermal comfort models for the elderly, and analyzes the characteristics and applicability of different models. At the same time, the important physiological parameters involved in the model are also summarized. This article identifies the current knowledge gaps, It provides some directions for the future research on thermal comfort and health of the elderly.

2. Thermoregulatory models for elderly people

Human thermoregulatory model includes a passive system and an active system. The skin temperature distribution and core temperature distribution of human body in different thermal environments can be predicted by inputting the ambient environment parameters and some human related parameters. In addition, combining this kind of model with thermal sensation model can predict the human thermal sensation at the same time. The models for the elderly are usually based on the existing thermoregulatory models for average adults, but modified some physiological parameters. A summary of these models is shown in **Tab. 1**.

Tab. 1 - Thermoregulatory models for elderly people

Model	Age	Basic model	Modification	
			Passive system	Active system
Novieto [17]	>75	Fiala's model	Modify Weight, Height, Body fat, Basic metabolic rate , Cardiac output	The coefficients of the equation are modified by Neural algorithm
Takahashi (JOS-3) [22]	>60	JOS-2 model	Modify Weight, Height, Basic metabolic rate, Body fat, Age, Sex, Add heat gain by shortwave solar radiation, Change the nodes of the pelvis	Add aging effect factors; Add non–shivering thermogenesis caused by brown adipose tissue
Rida [23]		Karaki's model	Modify Basic metabolic rate , Body fat(skin), Blood flow max(skin), Blood flow min(skin), Fat skin thickness	Modify sweat factor; Cold shivering factor; Threshold of thermoregulatory action; Arterial radii
Itani [25]	>60	Rida's model	Modify abdomen fat thickness	Modify body fat (skin) and the threshold of sweating are affected by the body water losses; Metabolic rate, heart rate and cardiac output are affected by the body core temperature
Hirata [26]	mean: 67.8 (elderly) 73.9 (aged)	Nagaoka's model	–	Modif sweating in the limbs(legs); Sensitivity of the skin due to aging affects the threshold of sweating
Zhou [30]	40-60	Fiala's model	Modify Weight, Height, Age, Sex, Segments' length and radius	–
Ma [35]	>60	Zhou's model	Modify Weight, Height, Age, Sex, Segments' length and radius(models for men and women separately)	–

Coccarelli [38]	<80	Coccarelli's previous model	Modify Age, Vessel wall elasticity, Heart rate, End-diastolic elastance, End-systolic elastance, End-diastolic pressure, Bone density, Segments' length and radius	Modify Thermal sensitivity factor; The maximum and minimum skin blood flow; The threshold of sweating

Based on the IESD-Fiala model [19], Novieto and Zhang [17, 18] modified the weight, height, percentage of body fat, basal metabolic rate and cardiac output of the passive system in the original model into the corresponding parameters of the elderly through literature research, and recalculated the body surface area through height and weight. For the active system, they did not change the node temperature set point in the original model, but modified the coefficients of the controling formulas in the original model through the Genetic algorithm [20]. This model was verificated in the 5-42°C conditions through the existing data in literatures. It was found that the accuracy of the model in predicting the core temperature was higher than that of the mean skin temperature.

Tanabe established a Jointed Circulation System (JOS) model for women and the elderly based on Stolwijk's model. The input parameters of the model include age, gender, basal metabolic rate and percentage of body fat. The AVA mechanism of hands and feet and the heat transfer in the superficial venous of limbs were also considered in the passive system. After that, the research team improved the JOS to the JOS-2 model [21]. JOS-2 model redivided the node of head in the passive system. In the active system, JOS-2 proposed different aging factors which would change the human thermal response, but did not give specific values. Recently, the research team updated JOS-2 to JOS-3 model [22]. In the passive system, the pelvic node was modified, and the heat production of short wave radiation was included, so that the model could more accurately predict the human body temperature in the solar radiation environment. Meanwhile, the non-shifting thermogenesis caused by human brown adipose tissue was added to the active system, making the prediction of metabolic rate more accurate. In addition, the model gave the specific value of aging factors proposed in JOS-2. The model was verified by simulation in steady and unsteady conditions. It is considered that it can more accurately predict the thermal response of young and older men in cold environment than JOS-2.

Rida et al. [23] established a biothermal model for elderly people based on the bioheat model of Karaki [24]. The passive system of this model considered a blood circulation model based on cardiac output and limb blood flow (including arterial and venous blood circulation, limb AVA mechanism and skin blood perfusion). Particularly, reseachers modeled each finger as independent segments to predict the finger temperature more accurately. In addition, the regulated skin blood perfusion coefficients, the metabolic rate during hot and cold conditions, and the cardiac output were also modified.It is verified that the model has certain accuracy in cold/heat stress environment. The Rida's model was further improved [25], to made it can be applied to predict the thermal response of the elderly in extremely hot environment. In the active system of this model, the changes of skin blood flow and sweating threshold caused by body water loss and the changes of heart rate, cardiac output and metabolic rate caused by the increase of core temperature were considered.

The model established by Hirata et al. [26] can predict the body temperature and sweating of elderly people exposed to passive heat. The passive system of the model was based on a voxel model [27], which had an anatomically realistic shape of human body. The passive system adopted Pennes's bioheat equation [28]. But when calculating the blood temperature, the total blood volume was simplified to 7% of the weight of the corresponding part. And for the blood perfusion rate, it was assumed that only the increased cardiac output can meet the increased demand for skin blood flow, while ignoring the potential redistribution of blood flow from internal organs to skin [29]. In addition, the model considers the change of sweating threshold caused by the change of skin sensitivity caused by aging in the active system. The model considers the maximum possible evaporation heat loss under hot conditions, and can predict the sweating rate and core temperature of the elderly.

Zhou et al. [30] modified some physiological parameters in the passive system of Fiala's model [31]. In particular, metabolic rate, percentage of body fat and cardiac output in the model were not independent input parameters, but calculated by gender, age, height and weight [32-34], which makes the model more personalized. Ma et al. [35] further modified Zhou's model [36, 37], refined the physiological parameters to each body segment in passive system, and made the model suitable for the elderly over 60 years old. Coccarelli et al. [38] built the model based on their previous thermoregulatory model [39], considered the changes of vascular elasticity, cardiac contraction and bone mineral density in the passive system caused by aging, as well as the changes of blood flow and sweating threshold in the control system.

3. Other models for elderly people

Different from the above temperature regulation and thermal sensation models, the adaptive thermal comfort model is based on the data measured in the field test, which focuses on reflecting the relationship between human thermal response (thermal comfort temperature, clothing insulation, regulation behavior, etc.) and outdoor climate parameters, reflecting the adaptability of different people to the local environment. The research results fully show the significant correlation between comfort temperature and outdoor temperature, that is, with local climate characteristics, especially with outdoor temperature [40]. A summary of these models is shown in **Tab. 2**.

Yang et al. [41] studied the effect of seasonality on the thermal comfort of the elderly in the elderly care center and found that the comfort range of the elderly was wider than expected by PMV. The elderly prefer warm or slightly hot indoor temperature. The linear regression equation between 4-day weighted running mean of outdoor temperature and clothing insulation of the elderly was established, Showing that the clothing insulation distribution of the elderly in mid season is wider and more diverse. And elderly people were more sensitive to outdoor temperature.

Wang et al. established an adaptive thermal adaptation model for older people (ATCO) through field investigation of a nursing home [42]. Comparing the Atco model with the neutral temperature of the elderly obtained by the adaptive model provided by ASHRAE and EN15251, it is found that the Atco model predicts a lower neutral temperature in the cold outdoor environment and a higher neutral temperature in the warm outdoor environment, which is more accurate than the other two models. The paper also compares the adaptive models of the elderly and adults, and finds that the neutral temperature of the elderly is higher. In the follow-up study, the research team established an adaptive model [43] for the middle-aged and elderly people in the house. It is considered that the acceptable temperature range for the elderly is 14.1-19.4 ℃ in winter and 23.8-27.0 ℃ in summer. In addition, the clothing model of the elderly in winter [44] is also established. It is pointed out that the wrong estimation of the thermal insulation of the typical winter clothing of the elderly may lead to the deviation of the predicted average skin temperature of about 1.3 ° C or the deviation of heat loss of about 26%.

Tab. 2 - Adaptive models for elderly people.

Model	Region	Age	Outdoor parameter	Thermal response
Yang [41]	Korea	>65	4-day weighted running mean of outdoor temperature	clothing insulation
Wang [42]	Shanghai, China	>70	7-day weighted running mean of outdoor temperature	Neutral temperature
Jiao [43]			Prevailing mean outdoor air temperature	Neutral temperature
Tang [44]			Outdoor air temperature	Clothing insulation
Wu [45]	Chongqing, China	>60	Outdoor air temperature	Thermal sensation vote, Proportion of air-conditioned, Proportion of windows opened, Proportion of fans used

Giamalaki [46]	Crete, Greece	>65	Monthly average temperature	–

Wu et al. [45] studied the elderly in residential buildings and nursing homes in Chongqing, and obtained the adaptability model of the elderly in this area. It is found that the thermal sensation of the elderly is affected by outdoor air temperature more than indoor air temperature. The elderly can sense the relative humidity of indoor and outdoor air. Moreover, in terms of adaptive behavior, natural ventilation (opening and closing windows) is the main way for the elderly.

Giamalaki et al. [46] considered the increase their expenditure of heating and cooling in the Adaptability Study of the elderly in Greece, and found that in the hot season, the elderly most often open windows to adapt to the environment, while in the cold season, they adapt by adjusting clothes. The elderly may first adopt strategies that do not require energy consumption, and then adopt methods to increase expenditure (such as using portable heaters and fans). However, the functional relationship between outdoor parameters and thermal behavior is not given, and only frequency statistics are carried out.

The research of Wang et al. [47] is based on the adaptive model APMV proposed by Yao et al. [48, 49]. Based on the survey and questionnaire survey of the elderly in Guiyang, China, the adaptive coefficient is obtained λ= 0.32. The actual thermal comfort temperature of the elderly is higher than that predicted by PMV model.

Machine learning model is the latest model, which depends on computer and sensor technology. The traditional thermal comfort model usually adopts the white box approach, while the machine learning model prefers to use the black box approach (e.g. linear SVM, radial basis function (RBF) SVM and random forest) to process a large number of data to predict human thermal comfort. Some studies show that the accuracy of the black box approach is better than that of the white box approach [50]. Few of the existing machine learning models [51-53] are suitable for the elderly. Wang et al. [54] established a machine learning model suitable for the elderly, using four environmental variables (air temperature, speed, CO2) concentration and illumination plus two human related variables (health status and residence time in nursing home) as input parameters to predict the thermal sensation of the elderly. It is verified that the accuracy of this model is 24.9% higher than that of PMV model.

4. Conclusion

For thermoregulatory models, based on the Fiala multi-node model, by correcting the height, weight, basal metabolic rate, body fat, segments' length and radius, blood vessel distribution in the passive system (among which, the basal metabolic rate, body fat and cardiac output are considered as a sensitive parameter), and the threshold of sweating and shivering temperature in the control system can more accurately predict the physiological parameters of the elderly (skin temperature, core temperature, sweating, etc.). Through these physiological parameters, thermal sensation can be predicted. Thermoregulatory models are widely applicable because they take environmental factors into account and include a detailed biological model of the human body. Although thethermoregulatory model takes clothing insulation into account, it lacks a dynamic model for clothing changes in the elderly and components for other behavioral responses, such as opening windows or not, using cooling devicest or not. In addition, the parameters used in the model are the average value of the older people, and lack of personalized parameters, so it cannot be better used to predict individual responses.

For thermal adaptation models, the connection between the outdoor environment and human behavioral responses is mainly established. At present, there are few studies, and they are mainly aimed at the elderly group in a certain climate environment or region, so the scope of application is small. In addition, the models rarely involve physiological parameters, so they lack a certain degree of objectivity. But the human behavior included in the thermal adaptation model may complement the thermoregulatory model.

Different from thermal regulation models and thermal adaptation modesl, machine learning models take more parameters (such as CO_2 concentration, individual health, etc.) as input parameters, and found that the black box method can predict thermal sensation more accurately than the white box method. However, the black box method cannot observe the intermediate process, which makes the output results difficult to interpret and affects the reliability of the model. In addition. These models require a large amount of data to support, and there are still few studies on thermal comfort of the elderly, so there are few machine learning models, and the scope of application is limited.

In general, among the existing thermal comfort models for the elderly, the thermoregulatory model can better predict the changes in the physiological parameters of the elderly, the thermal adaptation model can predict the behavior changes of the elderly, and machine learning models have higher accuracy in predicting changes in psychological parameters such as thermal sensation. Future research may consider the combination of models to predict the thermal response of the elderly more comprehensively and accurately.

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