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Development of a Data-Driven Predictive Model of Clothing Thermal Insulation Estimation by Using Advanced Computational Approaches

Kyungsoo Lee ¹, Haneul Choi ², Joon-Ho Choi ^{2,3} and Taeyeon Kim ^{2,*}

¹ Building Energy Center, Energy Division, KCL (Korea Conformity Laboratories), Seoul 27872, Korea; kslee@kcl.re.kr

² Department of Architecture & Architectural Engineering, Yonsei University, Seoul 03722, Korea; chn7960@yonsei.ac.kr (H.C.); joonhoch@usc.edu (J.-H.C.)

³ School of Architecture, University of Southern California, Los Angeles, CA 90089, USA

* Correspondence: tkim@yonsei.ac.kr; Tel.: +82-2-2123-5783

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Abstract: Clothing condition was selected as a key human-subject-relevant parameter which is dynamically changed depending on the user's preferences and also on climate conditions. While the environmental components are relatively easier to measure using sensor devices, clothing value (clo) is almost impossible to visually estimate because it varies across building occupants even though they share constant thermal conditions in the same room. Therefore, in this study we developed a data-driven model to estimate the clothing insulation value as a function of skin and clothing surface temperatures. We adopted a series of environmental chamber tests with 20 participants. A portion of the collected data was used as a training dataset to establish a data-driven model based on the use of advanced computational algorithms. To consider a practical application, in this study we minimized the number of sensing points for data collection while adopting a wearable device for the user's convenience. The study results revealed that the developed predictive model generated an accuracy of 88.04%, and the accuracy became higher in the prediction of a high clo value than in that of a low value. In addition, the accuracy was affected by the user's body mass index. Therefore, this research confirms that it is possible to develop a data-driven predictive model of a user's clo value based on the use of his/her physiological and ambient environmental information, and an additional study with a larger dataset via using chamber experiments with additional test participants is required for better performance in terms of prediction accuracy.

Keywords: clothing thermal insulation; thermal comfort; human subject experiment; body mass index; human factors; user-centered approach; data mining

1. Introduction

Maintaining a comfortable thermal environment for occupants in an indoor space is the most important goal of an heating, ventilation, and air conditioning (HVAC) system [1]. In order to evaluate thermal comfort, many indices have been presented, including effective temperature (ET), operative temperature (OT), standard effective temperature (SET), and even a thermoregulation model [2,3]. In particular, the predicted mean vote (PMV) model proposed by Fanger [4], applied to ASHRAE Standard 55 [5], is the most widely used for evaluating thermal comfort. The PMV model is based on a mathematical equation and is limited in that it does not reflect the physiological characteristics of each occupant [6]. Nonetheless, the PMV model is still the most-used model for thermal comfort evaluation and HVAC system control.

The PMV model evaluates thermal comfort by using six factors: air temperature, mean radiant temperature, relative humidity, air velocity, clothing thermal insulation, and metabolic rate. Among those six factors, the human factors, clothing thermal insulation and metabolic rate, are known to be difficult to measure. Accurate clothing thermal insulation can only be determined through precise measurements in the laboratory [7]. However, since this process is laborious, major international standards provide a table established by measuring the thermal insulation of several clothing items in advance [5,8], which has been significantly adopted by industry and academia. In practice, one [9,10], two [11–15], or three [16] clothing ensembles have been assumed and the total clothing thermal insulation calculated by referring to the tables to evaluate thermal comfort or control an HVAC system based on the PMV model.

However, in reality, clothing ensembles vary individually and seasonally [17,18]. In addition, a clothing ensemble could be changed within a short period of time with an option of putting clothes on or taking them off. Accordingly, the conventional method that adopts a fixed representational clothing (clo) value—without consideration of a clothing ensemble value, dynamically changing over time—may contribute to causing errors in thermal comfort prediction [19].

Evaluating the clo value dynamically is also important for energy savings. Newsham [20] reported that increasing clothing flexibility could affect energy consumption. Lee and Schiavon [21] showed that the energy analysis results for PMV model control could be incorrect when using a conventional method for applying 0.5 clo and 1.0 clo for the cooling and heating seasons, respectively.

Several recent studies have been conducted to predict clo values dynamically. De Carli et al. [22] and Schiavon et al. [11] constructed a model that predicts clo values based on the outdoor temperature at 6 a.m., because people mainly decide on their clothing ensemble according to the weather in the morning. However, these predictive models do not reflect the fact that occupants can change their clothing ensemble depending on the situation.

Some researchers used a heat balance model, rather than the outdoor temperature, to predict clo values in real time. M. Konarska et al. [23] measured the skin temperature of each part of the human body and applied these temperatures to the heat balance model to calculate the clo value. Lee et al. [24] and Miura et al. [25] suggested a predictive model for evaluating the clo value by measuring several local skin temperatures and clothing surface temperatures using an infrared camera and calculating the heat balance equation. These studies showed the possibility of using a predictive model to estimate clo values in real time. However, since the heat balance model adopted in the predictive models discussed above depends on predefined computational formulas, they have a significant limitation in that they do not consider individual physiological characteristics, such as body mass index (BMI) [26]. Previous studies have reported that the clothing thermal insulation predicted by the heat balance model was significantly different from the actual one [27–29]. In addition, many studies of thermal comfort [6,30–33] have proposed a more accurate model that predicts thermal comfort by using physiological factors.

In recent years, a data-driven approach has been actively used to evaluate personal thermal comfort by considering physiological factors [34]. Jiang and Yao [35] modeled the individual's thermal sensation using the C-support vector classification algorithm, which is a type of data-driven method. They showed that the accuracy of the predictive model was above 89% against the measured data. Ghahramani et al. [36] predicted the individual's thermal comfort using infrared thermography of the human face and collected thermal comfort votes. Through statistical analysis, this study revealed that four points of the human face—front face, cheekbone, nose, and ear—played an important role in predicting personal thermal comfort. Recently, Choi and Yeom [6] developed a data-driven thermal sensation prediction model as a function of local body skin temperatures. They showed that a combination of the waist, arm, and wrist (front), as well as BMI and gender, could be used to estimate overall thermal sensation with 95.87% accuracy. However, to the authors' knowledge, there has not yet been an attempt to estimate clothing insulation using data-driven methods, not thermal comfort.

Thus, the purpose of this study was to establish a data-driven model that predicts the clo value with the consideration of individual physiological factors in real time. A series of experiments in an environmental chamber with multiple test participants were carried out to measure the skin and clothing surface temperatures of each subject. The environmental conditions and individual physiological data of the subjects were applied by data-driven methods.

2. Methods

2.1. Experimental Chamber

In this study, human experiments were performed to measure each subject's local skin (forehead) and clothing surface (chest and thighs) temperatures. The forehead was selected as a representative body spot which shows the most significant relationship with whole-body thermal sensation, according to a recent study [6]. The experiments were conducted in a climate chamber located at Yonsei University, Seoul. The climate chamber measured $4.2\text{ m} \times 2.3\text{ m}$, and all walls were filled with insulation. The climate chamber (top view shown in Figure 1) can be controlled with a range of temperatures ($0\text{ }^{\circ}\text{C}$ to $60\text{ }^{\circ}\text{C}$, $\pm 1\text{ }^{\circ}\text{C}$) and relative humidity (1% to 99%, $\pm 10\%$) through an HVAC system.

Figure 1. Floor plan of the experimental chamber.

Environmental factors were measured every 5 s at heights of 0.1 m, 1.1 m, and 1.7 m. During the experiment, based on ASHRAE Standard 55, the temperature difference between the head (1.7 m) and the foot (0.1 m) was kept below $3\text{ }^{\circ}\text{C}$. The concentration of CO_2 was also kept below 1000 ppm, so that the subjects were not affected.

2.2. Experimental Instruments

Various sensors were used to measure the skin and clothing surface temperatures of each subject and the environmental variables. Skin and clothing surface temperatures were measured using a thermocouple, and a data acquisition board was used to provide the data for NI 9213 and NI-cDAQ 9178 instruments. The skin and clothing surface temperature measurements are shown in Figure 2. Environmental factors were measured using a Testo 480 from TESTO, Inc. The specifications of the measuring equipment are shown in Table 1.

Figure 2. Measuring the skin (forehead) and clothing surface (chest and thighs) temperatures.

Table 1. Specifications of the experimental instruments.

Measuring Variables	Experimental Instrument	Accuracy
Air temperature	Testo 480	$\pm 0.5\text{ }^{\circ}\text{C}$
Mean radiant temperature	Testo 480	$\pm 1.5\text{ }^{\circ}\text{C}$
Relative humidity	Testo 480	$\pm (1.8\% \text{ rh} + 0.7\% \text{ of measured value})$
Wind speed	Testo 480	$\pm (0.03 \text{ m/s} + 4.0\% \text{ of measured value})$
CO ₂	TSI IAQ-Calc M7515	$\pm (50 \text{ ppm or } 3.0\% \text{ of measured value})$
Skin and clothing temperature	Thermocouple T-type	$\pm (1.0\text{ }^{\circ}\text{C or } 0.75\% \text{ of measured value})$
Data acquisition board 1	NI-cDAQ 9178	Resolution: 32 bits, Sampling rate: 1.6 MS/s
Data acquisition board 2	NI 9213	Resolution: 24 bits, Sampling rate: 75 S/s

2.3. Experimental Procedures

The 20 subjects, who voluntarily participated in the experiment, were all healthy college students in their 20s. Information about the participants is shown in Table 2. They were asked to not eat or use caffeinated beverages for 1 h before the experiment, which was approved, in advance, by the Yonsei Institutional Review Board.

Table 2. Information on the human subjects.

Number of Test Participants	Body Mass Index (BMI)	Age	Height (cm)	Weight (kg)
20	21.6 ± 2.03	25.9 ± 1.73	173.2 ± 4.04	64.7 ± 6.37

For this study, a clothing ensemble for each season (winter, spring/fall, and summer) was selected, as shown in Table 3. A suitable clothing ensemble was selected for the indoor space, and a relatively light clothing ensemble of 1.0 clo, or less, was used. The clo value was calculated using Equation (1), as presented in ISO 9920 [7].

$$I_{cl} = 0.161 + 0.835 \sum I_{clu} \quad (1)$$

Table 3. Seasonal clothing ensembles.

Season	I_{cl} (clo)	Clothing Ensemble
Winter	0.96	Briefs, singlet, shirt, thick sweatshirts, sweatpants, and slippers
Spring/Fall	0.70	Briefs, singlet, sweatshirts, sweatpants, and slippers
Summer	0.41	Briefs, singlet, short-sleeve shirt, shorts, and slippers

The result of Equation (1) is expressed in clo, and I_{clu} is the effective thermal insulation of the individual garments making up the ensemble in terms of clo.

During the experiment, the subjects maintained a relaxed standing posture. The thermal insulation value of clothing can differ because of the amount of air between clothing layers [24,37–39] or properties of the clothing [40]. In a sitting position, some may be wrinkled or others may be folded, so there could be a different clo value. Therefore, the standing posture was maintained so that the clothing would not wrinkle and there would not be an unintentional air layer between clothing layers. A flowchart of the experiment is shown in Figure 3.

Figure 3. Flowchart of experiments.

The experiment then proceeded to the cooling process of each clothing ensemble. This procedure was as follows.

1. Subject wears the summer clothing ensemble in the climate chamber and adjusts to the set conditions (26 °C, 50% rh) for 10 min.
2. After adaption to the set conditions, each subject retains the standing posture for 5 min, and the skin and clothing surface temperatures are measured.
3. The subject sits and rests during a temperature change interval to match new set conditions (24 °C, 50% rh).
4. Steps 1–3 are repeated for each clothing ensemble in different conditions (For spring/fall clothing ensembles, a total of three experiments was conducted).

2.4. Data Analysis

The measured data and the physiological data of all subjects were statistically analyzed. All statistical analyses were performed at a 95% significance level. In this study, stepwise regression and a J48 decision tree were used to investigate the effects of variables on clothing thermal insulation. Data analyses were conducted using Minitab [41,42] and WEKA software.

2.4.1. Stepwise Regression Algorithm

Stepwise regression is based on a regression algorithm and is an automated technique that selects important predictive variables in order to construct a regression model [43]. In stepwise regression, forward selection to keep important variables and backward elimination to remove less important

variables are used [44]. In this way, predictive variables that describe the dependent variables can be identified in order.

2.4.2. J48 Decision Tree Algorithm

The decision tree is a significant data-mining method [45]. The distribution of a data set can be classified, and even a bulk data set can be easily understood by means of a decision tree. The J48 decision tree is based on WEKA. Developed at the University of Waikato, New Zealand, WEKA is open-source data-mining software under the GNU General Public License. The algorithm of a J48 decision tree can be easily split into a data set to find significant information [46].

3. Results and Discussion

3.1. Results of Human Subject Experiments

The skin and clothing surface temperatures of the subjects were measured in the human experiment. Physiological data, such as BMI, as well as skin and clothing surface temperatures, were collected in predicting clothing thermal insulation. BMI data are physical characteristics that differ from person to person. Therefore, many studies on thermal comfort [30,31,47] have proposed a more accurate thermal comfort prediction model using BMI. This study also tried to improve the accuracy of clothing thermal insulation prediction by considering the different physical characteristics of each subject.

3.2. Skin And Clothing Temperatures

Skin and clothing surface temperatures were classified according to the clo value and air temperature, as shown in Figures 4–6. The measurements showed that skin temperature increased as the clothing thermal insulation increased given the same air temperature. Also, the higher the air temperature, the lower the skin temperature. Therefore, it was found that the skin temperature showed a positive correlation with the clothing thermal insulation and a negative correlation with the air temperature. These results are due to the physiological phenomena of the human body, which exchanges heat with the surrounding environment [1]. The human body adopts thermoregulatory mechanisms to maintain its core temperature while varying the skin temperatures over the body [2]. When the temperature around the human body is lowered, the human body minimizes the sensible heat loss to the surrounding environment through various activities, such as shivering and vasoconstriction [5]. In addition, when the air temperature rises, perspiration and vasodilation prevent the core temperature from rising.

It was found that the top clothing surface temperature decreased with increasing clo value, even at the same air temperature. The ratio of top clothing surface temperature decrease to the increase in clothing thermal insulation became lower when the air temperature got higher. However, there was no correlation with air temperature under the same clothing conditions.

The bottom clothing surface temperature also increased as the clo value increased at the same air temperature and, likewise, was not correlated with the air temperature. The rate of increase in bottom clothing surface temperature to the increase in clothing thermal insulation proportionally increased when the air temperature increased. Each top and bottom item of clothing chosen has different materials and properties that depend on the season. As a result, the top and bottom clothing surface temperatures show different correlations that depend on the clo value.

Figure 4. Interval plot of skin temperature by clo value and air temperature.

Figure 5. Interval plot of top clothing temperature by clo value and air temperature.

Figure 6. Interval plot of bottom clothing temperature by clo value and air temperature.

3.3. Predictive Model of Clothing Thermal Insulation

3.3.1. Predictive Model Using the Stepwise Regression Algorithm

In this study, the training dataset comprised 70% of the experimental results of the 20 subjects; the remaining 30% were used for the test dataset. Thus, a stepwise regression model was constructed using the training data. Skin and clothing surface temperatures, BMI, and experimental conditions such as Ta (air temperature), MRT (mean radiant temperature), rh (relative humidity), and V (air velocity) were used. The stepwise regression results are shown in Table 4. The stepwise regression showed that Ta was the most significant variable, with R^2 of 34.59%. The R^2 values of the bottom and top clothing surface temperatures were 14.97%, and 14.89%, respectively. BMI showed the fourth highest R^2 of 7.19%. As a result, 73.83% of the distribution of the data can be explained by air temperature, skin and clothing surface temperatures, and BMI.

Table 4. Stepwise analysis of all variables and clo values.

	Step 1		Step 2		Step 3		Step 4		Step 5		Step 6		Step 7	
	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
Ta	−0.096	0.000			−0.061	0.000	−0.054	0.000	−0.035	0.000	−0.084	0.000	−0.084	0.000
Tcl_bottom			−0.090	0.000	−0.124	0.000	−0.143	0.000	−0.138	0.000	0.128	0.000	0.127	0.000
Tcl_top			−0.092	0.000	−0.124	0.000	−0.144	0.000	−0.137	0.000	−0.140	0.000	−0.141	0.000
BMI							−0.024	0.000	−0.017	0.000	−0.017	0.000	−0.016	0.000
Tsk									0.059	0.000	0.050	0.000	0.049	0.000
MRT											0.036	0.000	0.033	0.000
rh													−0.002	0.000
R-sq	34.59%		49.56%		64.45%		71.64%		73.83%		74.44%		74.80%	
Δ R-sq			14.97%		14.89%		7.19%		2.19%		0.61%		0.36%	

Equation (2) is the result of the stepwise regression algorithm. The test dataset was used for the regression equation to validate the predictive model of clo values. Figure 7 is an interval plot of the predicted results of six validation datasets using the stepwise regression algorithm. Figure 8 shows the results of the predicted clo values of the six individuals classified by the test dataset.

Figure 7. Interval plot of predicted clo level (six test datasets).

Figure 8. Interval plot of predicted clo level (Subjects 1–6).

As a result, a winter clothing ensemble (0.96 clo) was predicted to be 0.94 clo. Also, spring/fall (0.70 clo) and summer (0.41 clo) clothing ensembles were predicted to be 0.76 clo and 0.52 clo, respectively.

The performance of the predictive model was improved as the clo value increased. In particular, for the winter clothing ensemble, the predicted value was almost the same as the actual clo value.

$$\begin{aligned} \text{clo} = & 1.280 - 0.016339\text{BMI} - 0.08356 T_a + 0.03339 T_r - 0.001840 r_h \\ & + 0.0493T_{sk} - 0.14107T_{cl(top)} + 0.12714T_{cl(bottom)} \end{aligned} \quad (2)$$

3.3.2. Predictive Model Using the J48 Decision Tree Algorithm

In this study, clo value was predicted using a decision tree algorithm in addition to the stepwise regression algorithm. The data from the experiments were also divided into 14 training datasets and 6 test datasets as in the predictive model using the stepwise regression algorithm. The predictive model was constructed with the training dataset and validated with the test dataset. In order to facilitate classification using the decision tree algorithm, each numerical clo value was converted to nominal data (0.41 clo for Low; 0.70 clo for Mid; 0.96 clo for High).

The significant attributes were combined to predict the clo value according to the stepwise regression analysis. The combined attributes were applied to the J48 decision tree to predict the clo value. Table 5 and Figure 9 show the accuracy of the combinations. The accuracy was 69.46% when the clo value was predicted from the air temperature, which was identified as the most important variable in the stepwise regression analysis. Air temperature was an important variable in predicting the clo value in the J48 decision tree analysis, as well as in the stepwise regression analysis. Like when Schiavon and Lee predicted clo values in outdoor temperatures and operative temperatures, this study also showed that air temperature is an important variable in predicting clo values.

Table 5. Accuracy of decision trees according to combinations of attributes.

Combination of Attributes		Accuracy (%)
A	Ta	69.46
B	Ta and Tcl_b	65.02
C	Ta, Tcl_b, and Tcl_t	80.44
D	Ta, Tcl_b, and Tcl_t, and BMI	88.04
E	Ta, Tcl_b, Tcl_t, BMI, and Tsk	75.77
F	Ta, Tcl_b, Tcl_t, BMI, Tsk, and Tr	74.87
G	Ta, Tcl_b, Tcl_t, BMI, Tsk, Tr, and rh	76.16
H	Ta, Tcl_b, Tcl_t, BMI, Tsk, Tr, rh, and V	76.16

Figure 9. Accuracy of decision trees according to combinations of attributes.

According to the results of the stepwise regression analysis, the accuracy was improved when each attribute was added to the air temperature. The combination of air temperature, bottom clothing surface temperature, top clothing surface temperature, and BMI showed the highest accuracy (88.04%). The accuracy was lowered as other attributes were added to this combination. The decision tree using this combination is shown in Figure A1. The accuracy of the combination of air temperature with the top and bottom clothing surface temperatures was 80.44%, but it was increased by 7.60% when BMI was added. Therefore, BMI plays an important role in predicting the clo value. On the other hand, when the skin surface temperature was added, the accuracy was decreased. Skin surface temperature has been used as a predictor of thermal comfort in many studies, as has the forehead temperature used in this study. Nonetheless, we found that skin surface temperature does not play an important role in predicting clo values, presumably because the activity of the subject was controlled in this study. MRT, rh, and V also did not play an important role in predicting clo values.

Table 6 shows the accuracy of the decision tree for the combination of air temperature, top and bottom clothing surface temperatures, and BMI, which was the most accurate. As a result of the J48 decision tree, the precision of Low (0.41 clo) was evaluated as 0.8679, that of Mid (0.70 clo) was 0.8941, and that of High (0.96 clo) was 0.8733. The overall accuracy of the predictive model using the J48 decision tree was 88.04%. Therefore, clo values can be predicted by using the model proposed in this study.

Table 6. Confusion matrix of classified clo values.

		Classification		
		Low	Mid	High
clo	Low	565	70	0
	Mid	86	937	110
	High	0	41	758
Precision		86.79%	89.41%	87.33%

3.4. Prediction Accuracy By BMI

In stepwise regression and the J48 decision tree analysis, BMI showed a significant role in predicting clo values. BMI is classified into four groups by the WHO (World Health Organization). Table 7 shows the results of the classification of subjects participating in the experiment according to WHO. In this study, the two high/low groups were classified based on a BMI of 22. Therefore, the predicted results according to BMI were compared, and the importance of BMI in predicting the clo value was identified.

Table 7. BMI classification of subjects by WHO.

BMI	Range	Subjects
Underweight	18.5	1
Normal weight	18.5–24.9	16
Overweight	25.0–29.9	3
Obese	30	0
Total		20

Figure 10 is an interval plot of skin surface temperature according to the clo value, air temperature, and BMI. Figures 11 and 12 show the interval plot of the clothing surface temperature according to clo value, air temperature, and BMI. As shown in Figure 11, skin temperature was higher in groups with lower BMI in all cases, irrespective of clo value and air temperature. The difference in skin surface temperature between the two BMI groups did not change significantly with clo value and air temperature. For the low clo value (0.41 clo), the top clothing surface temperature of the group with a high BMI was low, but this was reversed for the high clo value (0.96 clo). As a result, the

top clothing surface temperature showed no correlation with BMI. In contrast, the bottom clothing surface temperature was higher in all cases with higher BMI. Therefore, the bottom clothing surface temperature and BMI were positively correlated.

Figure 10. Interval plot of skin temperature by clo value, air temperature, and BMI.

Figure 11. Interval plot of top clothing surface temperature by clo vlaue, air temperature, and BMI.

Figure 12. Interval plot of bottom clothing surface temperature by clo value, air temperature, and BMI.

Figure 13 shows predicted clo values by BMI according to the stepwise regression. Table 8 compares the accuracy of the predicted clo values for each BMI group. The error for the group with high BMI was higher than that for the group with low BMI at all clo value conditions. The error between the two groups was less than 3.13% for the high clo value (0.96 clo). In this study, the BMI values of the subjects were not significantly different. Therefore, the difference in accuracy in these groups is low.

Figure 13. Interval plot of predicted clo values by BMI.

Table 8. Error in predicted clo values by BMI.

BMI	Clo Value					
	0.41		0.7		0.96	
	High	Low	High	Low	High	Low
Predicted clo	0.53	0.52	0.77	0.76	0.91	0.98
Δ (Predicted clo – actual clo)	0.12	0.11	0.07	0.06	0.05	0.02
Error	29.27%	26.83%	10.00%	8.57%	5.21%	2.08%

4. Conclusions

The clo value plays an important role not only in thermal comfort but also in energy saving. In this study, a predictive model that can predict the clo value in real time was developed. To this end, the environmental factors and individual factors of subjects were measured in various clothing conditions through the human experiment. The data obtained from the experiment were applied to the stepwise regression and decision tree algorithms. The results of this study are as follows.

1. The predictive model using the decision tree algorithm showed an accuracy of 88.04% when using air temperature, top and bottom clothing surface temperatures, and BMI.
2. For both predictive models, the higher the clo value, the higher the precision of the clo value prediction.
3. According to BMI group, there was a difference in the accuracy of the clo value prediction model, especially for the highest clo value (0.96 clo).

For practical application of the predictive model established in this paper, it is necessary to obtain various data, such as skin temperatures and clothing temperatures, in real time. Such a practical application can be technically implemented by the use of sensory devices, such as infrared cameras and PMV meters, which have been frequently adopted in existing studies [23–25]. In recent years, sensor technology has been developed, and inexpensive sensors with good performance have been introduced. Therefore, considering that these sensors will be actively used in the future, the results of this research have high potential to be adopted for evaluating individual clothing insulation and, furthermore, thermal comfort in real time. Also, it is necessary to reduce the number of sensing points and simplify the computational algorithm to achieve a cost-effective approach.

In this study, the predictive models were constructed through a data-driven method, but there were limitations. Twenty human subjects were used as a sample, and a statistically meaningful deduction resulted. However, a larger sample size would have increased the accuracy and validity of the results, especially considering the differences in BMI. The experiment was carried out only for cooling. Therefore, it is necessary to carry out the experiment using heating in the future. In addition, only three clothing ensembles were selected for each season. In the future, it will be necessary to construct more sophisticated prediction models by using more clothing ensembles with a larger dataset for better performance.

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Appendix A

Figure A1. Decision tree with air temperature, top and bottom clothing surface temperatures, and BMI (graphic-based classification model).

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