Hindawi
Advances in Civil Engineering
Volume 2024, Article ID 2106137, 14 pages
https://doi.org/10.1155/2024/2106137

Research Article

The Personalized Thermal Comfort Prediction Using an MH-LSTM Neural Network Method

Jaeyoun Cho,[1] Hyunkyu Shin ,[2] Yonghan Ahn,[3] and Jongnam Ho[1]

[1]*Department of Smart City Engineering, Hanyang University, Ansan 15588, Republic of Korea*
[2]*Division of Architecture, Mokwon University, Daejeon 35349, Republic of Korea*
[3]*Department of Architectural Engineering, Hanyang University, Ansan 15588, Republic of Korea*

Correspondence should be addressed to Hyunkyu Shin; shinhk@mokwon.ac.kr

Received 10 October 2023; Revised 12 January 2024; Accepted 22 March 2024; Published 18 April 2024

Academic Editor: Robert Černý

As demand for indoor thermal comfort increases, occupants' subjective thermal sensation is becoming an important indicator of the building environment. Traditional models like the predicted mean vote-based model may not be reliable for individual comfort. This study proposed the multihead long short-term memory (LSTM) model to reflect physical and environment-driven data variation. Controlled experiments were conducted with individual temperature measurements of six participants, and the collected data showed significant potential to predict individual thermal comfort using a model trained for each person. The results derived from this study can be utilized, in future, for predicting the thermal comfort and for optimizing the thermal environments using personal body temperature and surrounding environmental data in a space where mainly independent activities are performed. This study contributes to the relevant literature by suggesting a method that predicts thermal comfort based on the multihead LSTM method.

1. Introduction

Ensuring thermal comfort in indoor environments has become increasingly important with the rise in indoor activity time [1]. This requires exceptional performance to ensure the protection and safety of people living and working within the building [2]. And the satisfaction of occupants with regard to thermal comfort is an essential function of the building environment [3]. The perception of thermal comfort is a key factor in determining the indoor environmental quality of spaces such as offices, hospitals, and homes [4–6]. The heating, ventilation, and air conditioning (HVAC) systems that operate with predefined set points derived from the predicted mean vote ((PMV) American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)) approach, which is a steady-state approach developed by Fanger [7], are a key factor in achieving thermal comfort. However, the conventional approach cannot thoroughly satisfy an occupant's perception of thermal comfort because it can be controlled by adjusting the indoor environment, such as temperature and humidity, with set schedules [8]. Although the PMV, as an international thermal environment indicator, is the most widely used mathematical method based on the current standards pertaining to thermal comfort, it has limitations in providing occupants' equivalent comfort because thermal comfort is subjective [1, 9, 10].

Several studies have shown that the classic PMV model has inconsistencies in predicting the thermal comfort sensation of the indoor environment [11–13]. Several studies have highlighted inconsistencies in the classic PMV model's ability to accurately predict thermal comfort in indoor environments. For example, Nicol [11] found that the international standard for indoor climate did not adequately describe comfortable conditions, and Alotaibi et al. [6] identified a significant difference between the thermal sensation vote (TSV) and the PMV of patients in air-conditioned environments in hot climates. The difference between thermal comfort sensation and PMV is due to the varying approaches used to determine thermal comfort for providing thermal environments. However, thermal comfort is subjective and closely related to the occupants' expectations and capacity to adapt. Therefore, the current system utilizes a rational approach to predict thermal comfort [5, 9, 14].

Another limitation of previous models is that they were designed for shared spaces, aiming to satisfy many people simultaneously. Therefore, existing systems are limited in their ability to predict individual optimal comfort temperatures [15]. To address these limitations, it is essential to develop a personalized thermal comfort model that considers specific metabolic characteristics to analyze individual preferences. Choi and Loftness [16] suggested using human body skin temperature to represent an individual's thermal sensation in a thermally uniform environment, indicating the potential for personalized models. Chaudhuri et al. [17] predicted the thermal state (discomfort/comfort) of occupants based on skin temperature and its gradient. Aryal and Becerik-Gerber [18] proposed machine learning algorithms to predict thermal comfort sensations and utilized wearable devices that sense physiological information to improve the prediction of individual thermal comfort levels. The results showed that controlling the current system based on personalized thermal comfort models that consider occupant responses could be more efficient in predicting thermal comfort levels than setting various standards as space characteristics [3, 18]. Recently, thermal comfort interpretation has shifted from space-centered to individual-centered, and the individual-oriented thermal comfort prediction model was developed under the premise that different occupants may have different perceptions of thermal comfort, even when exposed to the same environment [19]. The personalized thermal comfort model is not a stationary model but an adaptive and intelligent model based on the comfort level defined based on individual reactions. The thermal history, whether long-term or short-term, can influence the current thermal comfort sensation of occupants [20]. With the hypothesis that adaptive thermal comfort is affected by contextual and psychological factors, this study proposed a bioresponsive thermal comfort model with an environmental constant (time series) dataset collected from laboratory experiments. Thus, these facts imply deviations regarding the psychological adaptation of individual occupants. Hence, the moment environment data, long short-term changes in the indoor environment, and the body's response must all be considered to predict the sensitive thermal comfort level of individuals. Therefore, in this study, we propose a methodology that considers previous environmental information and aims to enhance existing approaches for predicting thermal comfort indicators. In order to predict the thermal comfort of residents, general sensors and flexible sensors were used to collect the indoor environment and bioreaction information of each resident as key parameters. To validate the effectiveness of the proposed model in determining individual thermal comfort levels, several subjects were studied in the same space and environments.

2. Literature Review

Previous studies have extensively investigated the thermal comfort sensation of occupants in indoor environments and proposed environmental prediction models based on the PMV [4, 5]. These models typically use six key variables to calculate PMV, including air temperature (ta), mean radiant temperature (tr), air velocity (va), relative humidity (rh), occupant metabolic rate (me), and clothing value (cl) [4]. Despite its widespread use in thermal comfort standards, predicting thermal comfort sensation in real-world situations using the conventional model remains challenging due to the discrepancy between PMV and thermal comfort sensation [4, 5]. To address this issue, Lai et al. [20] introduced the concept of adaptive PMV, and several experiments have since been conducted based on this theory during field studies [5, 9, 15, 21–26]. As shown in Table 1, many researchers have made significant efforts to predict thermal comfort. Thermal comfort is the subjective perception of the occupants without sweating [32].

To address the limitations of the existing PMV model, several studies [3, 15–18] have developed adaptive thermal comfort models that consider physical, physiological, and psychological factors in various environments. While these improved models provide optimal results for each setting, designing a thermal comfort model requires different standards depending on the environment and specific space settings. Consequently, the complex variables involved in the model make it challenging to collect various types of data.

The adaptive approach to thermal comfort refers to people's ability to restore comfort in response to changes in the environment through adaptive actions that link them to the building or other external factors such as outdoor climate, time, and building design. Many studies have examined the effects of adaptation on thermal sensation. For instance, Fountain et al. [23] found that people's thermal sensations and preferences are influenced by their thermal expectations, while Yao et al. [24] determined that self-regulatory actions, including physiological, psychological, and behavioral adaptations, can alleviate discomfort. Additionally, Nikolopoulou and Steemers [25] explored the impact of psychological adaptations, including perceived control, expectations, environmental stimulation, naturalness, time of exposure, and experience. Yao et al. [24] presented a comprehensive adaptive model of thermal comfort that considers cultural, climatic, social, psychological, and behavioral factors. Moreover, Jowkar et al. [26] found that different climatic backgrounds and long-term exposure to thermal conditions influence occupants' thermal expectations and may result in differences in their thermal sensation.

Li et al. [5] proposed a PMV model with an adaptation table to reduce the discrepancy in predicting thermal sensation and identified five effective variables (season, climate, building type, age group, and gender) through a meta-analysis. However, this model has limitations in providing a uniform thermal experience and climatic background for an unspecified number of occupants. Since the parameters affecting thermal comfort, such as outdoor climate, thermal expectation, age, and gender, are subjective and vary from person to person, calculating the PMV for general thermal comfort is challenging. To overcome these limitations, Buratti et al. [33] proposed a simplified approach that only considers temperature and relative humidity and is useful when only air temperature and relative

Table 1: Previous studies.

Author	Research scope	Target	Highlighted factors F1	F2	F3	F4	F5	F6	Research methodology
Yao et al. [24]	Self-regulatory actions	Psychological factor	—	—	○	—	—	—	Survey and monitoring
Jowkar et al. [26]		Thermal exposure	—	—	○	—	—	○	Field study, classification, and data analysis
Xiong et al. [27]	Physiological parameter	Investigated gender differences	○	—	○	○	—	—	Experiment
Choi and Yeom [28]		Local skin temperatures	○	—	○	○	—	○	Monitoring
Chaudhuri et al. [29]	Machine learning	Predicted thermal state (PTS)	—	○	○	—	—	○	Machine learning
Cosma et al. [30]		Individual thermal preference model	○	○	○	○	—	○	Experiment
Katic et al. [31]		Artificial neural network algorithm	—	○	—	—	—	○	Data analysis

Note. F1 = skin temperature; F2 = artificial intelligence approaches; F3 = gender; F4 = sensor device; F5 = individual characteristics; F6 = prediction of thermal comfort.

humidity data are available. However, this approach does not account for individual characteristics of occupants. Li et al. [5] emphasized that thermal comfort should consider occupants' responses. Chaudhuri et al. [29] presented a predicted thermal state (PTS) model that uses skin temperature as a physiological parameter. They argued that since previous studies [34, 35] have shown that skin temperature has a significant effect on an individual's thermoregulation principle, direct investigation of skin temperature may be a simpler approach to predicting thermal sensation [29].

In recent years, several studies have used both thermal comfort and skin temperature data to predict human thermal states. Chaudhuri et al. [17] developed a data-driven thermal state prediction model using physiological information, and they investigated gender differences in thermal perception. Similarly, Choi and Yeom [28] developed a data-driven thermal satisfaction prediction model using heart rate and seven local body temperatures with 18 participants. Aryal and Becerik-Gerber [18] demonstrated that combining data from environmental and physiological sensors is more accurate than using environmental sensors alone.

More recently, artificial intelligence approaches such as machine learning and deep learning have been explored as a novel way to predict thermal sensation. For example, Cosma and Simha [30] introduced a machine learning method to predict individual thermal preferences, while Katić et al. [36] used a feedforward network with 12 hidden neurons to predict personalized heating settings using air temperature, humidity, and radiant temperature as input features. However, these approaches did not consider personal physiological responses such as skin temperature gradients.

Previous studies have established significant correlations between overall thermal satisfaction and skin temperatures using various methods. However, these models have limitations in reflecting individual thermal expectations during long-term and short-term variations in dynamic environments. Additionally, feedforward-based networks have challenges in considering time-series environmental information and occupants' biometric data.

Human beings can adapt to changes in the environment [37], and past experiences can affect present comfort levels. As such, individual thermal comfort can vary based on short-term and long-term changes in the indoor environment. However, previous intelligent approaches for predicting the comfort index only used data measured at a single point in time to predict the target value.

To accurately represent the comfort index of the occupants, it is necessary to consider the environment to which they have been previously exposed. Therefore, this study proposes an advanced thermal prediction model capable of processing time-series datasets that consider current and past environmental information. We use a recurrent LSTM model, and the next section provides a detailed description of the model.

3. Research Methodology

To investigate the hypothesis pertaining to influence of the biometric data such as skin temperature on thermal comfort, this study developed a bioreactive PMV model using an LSTM network, and the proposed model was applied to experiments in an office space exposed to diverse environments. The LSTM network adopted in the model is a special type of deep learning model that can memorize the trend of data through a memory line incorporated in a network [38]. However, for modeling long-time exposed environments, such as variations in temperature and humidity, LSTM needs to retain the useful features for both long and short periods of time. Thus, this study applied the multihead approach to the LSTM model, which can extract valuable information with different timescales for accurate prediction of thermal sensation.

4. LSTM Network Design with Multitimescales

Volatile data constantly perceived from the indoor environment can influence the occupant's thermal sensation. Furthermore, individual perceptions of indoor environments vary significantly due to the subjective characteristics of human physiology, and these differences can affect thermal comfort [39]. Thus, considering of both the contexts of indoor environmental factors and the various physiological factors of individuals, a distinct model that is capable of operating a recurrent training mechanism is required. Classic deep neural network methods, such as feedforward

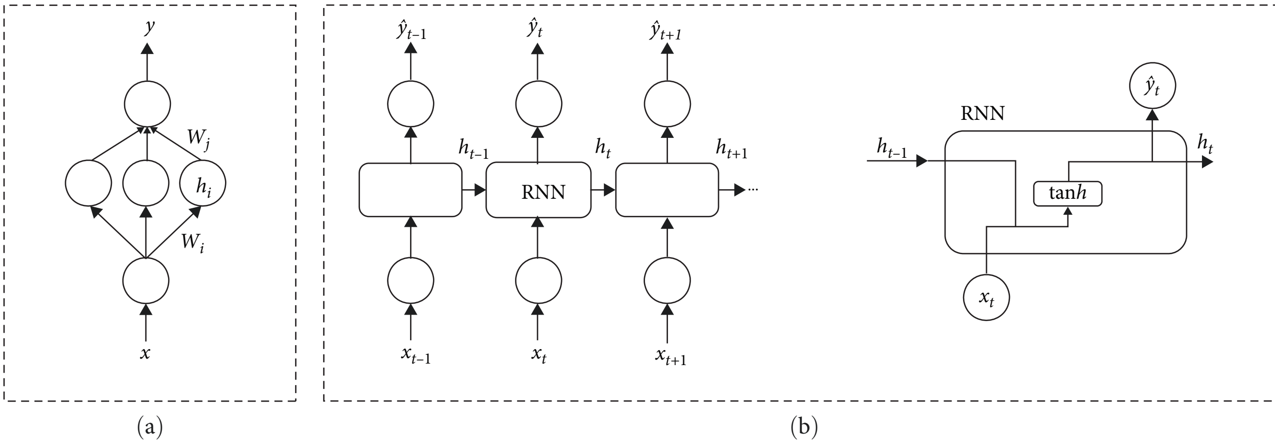

Figure 1: (a and b) Comparison of information processing between RNN and FFNN.

architectures, are commonly used to determine the forecasting sequence in the literature [40–43]. However, these approaches operate using the current input data, and consequently, the feedforward neural network (FFNN) cannot consider the interrelationship between the temporal dependencies of indoor environment and psychological changes. The lack of consideration for interrelationship between the time sequences makes it difficult to recognize the relationship between thermal comfort and environmental variations, and it is likely to limit an elaborate thermal comports prediction in space sensitive to environmental changes.

In contrast, a recurrent neural network (RNN), unlike standard FFNN, provides a solution using an internal state that stores previous contextual information in sequential time steps [44]. The RNN is specially designed to preserve information adopted in the previous time steps. The potential characteristics of the differences between the conventional FFNN and the general concept of RNNs were investigated and are presented in Figure 1.

As shown in the structure of the RNN, the hidden units (h_t) receive output from the previous hidden units (h_{t-1}) and calculate the current hidden unit (a_t) at time step, t, with input variables (x_t). In order to obtain the probabilities of vector ($\hat{y}_t$), the output (o_t) is used as an argument for the activation function. The current hidden unit in the forward pass can be defined using the following equations:

$$a_t = w_h h_{t-1} + w_x x_t + b_a, \tag{1}$$

$$h_t = \tanh(a_t), \tag{2}$$

$$o_t = w_o h_t + b_o, \tag{3}$$

$$\hat{y}_{t,i} = \frac{\exp(o_{t,i})}{\sum_{j=1}^{n} \exp(O_{t,j})} \text{ for } i = 1, 2, \ldots k, \tag{4}$$

$$\hat{y}_t = \text{softmax}\,(a_t). \tag{5}$$

Unlike conventional neural networks, hidden layers in the form memory cells are involved in recursive activity using a previously calculated output in each time step. Thus, RNNs that compute sequence data can address long-term sequential patterns using backpropagation through time, which provides a context with respect to inputs which can be considered according to the time stream. The recurrent approach has the advantage of finding valid features in the hidden pattern of a dataset. Nevertheless, its capability in training long-term dependency reveals the limitations of vanishing gradients [45].

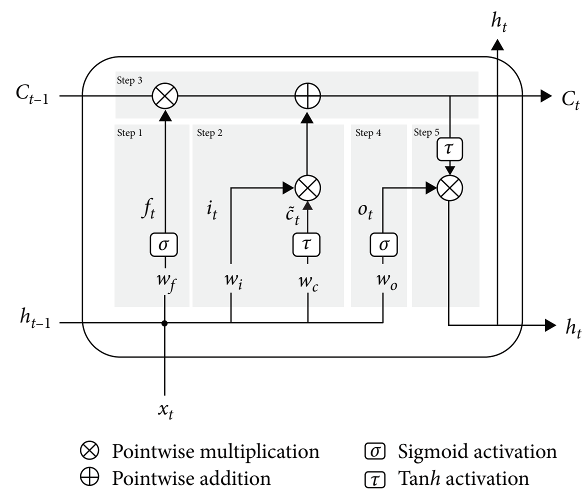

Figure 2: LSTM block calculation diagram.

To solve the limitation of vanishing gradients of long-term sequence features, LSTM was introduced by Hochreiter and Schmidhuber [46]. The main idea of the LSTM mechanism is to preserve long sequential information by using an additional cell state that can constantly retain the previous features. The LSTM unit overcomes the traditional RNN gradient vanishing problem by controlling the four main gates: forget, input, update, and output, as shown in Figure 2. The equations for each gate are illustrated below along with the LSTM block calculation diagram (Figure 2).

The first stage (i.e., the forget gate), determines the amount of information that requires removal from the previous memory cell to the current cell gate. In other words, it is a preservatory gate to decide how much information must be retained to consider the past context using the following equation:

$$f_t = \sigma\left(w_f h_{t-1} + w_f x_t + b_f\right). \quad (6)$$

The second stage involved reflecting on the information of the step t and storing it in the current cell state with the following two functions: the input gate (i_t) and candidate memory ($\tilde{c}_t$). Ct is the same that of the RNN.

$$i_t = w_h h_{t-1} + w_x x_t + b_a, \quad (7)$$

$$\widetilde{c}_t = \tanh\left(w_c h_{t-1} + w_c x_t + b_c\right). \quad (8)$$

Then, the new cell state (c_t) can be calculated using Equation (9) by updating the previous cell state (Ct−1) and considering both the input values and the candidate memory.

$$c_t = \tanh\left(f_t c_{t-1} + i_t \widetilde{c}_t\right). \quad (9)$$

Then, the output was decided on the basis of the filtered cell state as follows:

$$o_t = \sigma\left(w_o h_{t-1} + w_o x_t + b_o\right). \quad (10)$$

In this step, the output gate (o_t) determines the parts of the cell state that will be produced as the output. This cell state goes through the tan$h$ layer, so the values lie between (−1 and 1), and multiplies it by the output gate as follows:

$$h_t = o_t \tanh\left(c_t\right). \quad (11)$$

This gate was calculated as an output of the LSTM unit.

As described above, the cell state of the LSTM architecture can preserve past information and reflect the features by combining the current input data. This helps to avoid the problem of vanishing gradients in training long-term sequence data. In indoor environments, environmental data, such as temperature and humidity, change with time. Thus, this contextual information could be a crucial factor in predicting thermal comfort sensation. Jowkar et al. [26] determined that the thermal comfort of occupants staying in the same space for a long time is influenced by both short-term and long-term environmental changes.

Consequently, this study applied the theoretical fundamentals of the LSTM cell state, which considers both long-term and short-term environmental changes combined with the physiological changes of occupants in diverse-term sequences. From a diverse time step perspective, this model includes thermal sensations, including the context of environmental changes. Although this study addressed diverse daily time sequences, the proposed model can be applied to long-term time-sequence data from second units to date units. Furthermore, this study proposed a time-sequence adaptable neural network using a multihead timescale approach.

5. Model Development

Multiheaded neural network models have recently been proposed in the literature [47, 48]. Multitimescale LSTM is used to reflect various time periods while retaining the useful features with different sequence data [47, 48]. This approach can improve the performance of the recurrent model by training several spectrums of indoor environmental data. The multiheaded LSTM is used for different time sequences, and the features of each head are combined in fully connected layers to consider both short and long periods of indoor environmental context. Figure 3 shows the schematic design of the model proposed in this study.

Figure 3 shows a general overview of the multihead LSTM architecture used for independent PMV in this study. This architecture employs a multihead input data into the recurrent layers of the LSTM. Each LSTM cell is operated separately according to the length of the sequence; then, the outputs of each cell are concatenated in the fully connected layer. A specific part of the multihead process provides more information for training the model, where multivariate variables are inserted stepwise into the model to predict the target features. Hence, we can consider multiple time sequences that the occupants are exposed to in an indoor environment. For predicting the thermal comfort sensation using the multihead LSTM model proposed in this study, the experiments were designed to collect the physical and bioresponse-driven sources of variation from diverse indoor environments.

The model is used to collect the datasets of both indoor environment data and the metabolic data of occupants exposed to dynamic indoor temperature. The data were divided into four layers using a total of four sensors for both hands and indoor temperature and humidity measurement. Thus, in this study, the experimental design focused on collecting datasets from subjects exposed to several environments. Because PMV is different for each person, a model that is optimized using individual data is more accurate, efficient, and more suitable for predictions than optimizing a model by integrating multiple data (Figure 4).

6. Instrumentation and Experiment Scenario

The experiment was carried out from December 14, 2019, to January 12, 2020, which is typically wintertime in Korea. It is an optimal environment for experimenting with changes in room temperature. The experimental subjects included six people, and the indoor environment parameters, that is, indoor temperature and humidity, were recorded at intervals of 2s. The bioresponsive data were simultaneously recorded at 1s intervals using a flexible sensor [49] to determine the skin temperature in the back of the hand, which is correlated with heat sensations. The measurement instruments used in the experiments are listed in Tables 2 and 3. The individual thermal sensation was determined via subjective thermal comfort surveys every 5 min based on the following ASHRAE 7 point scale: −3 (cold), −2 (cool), −1 (slightly cool), 0 (natural), +1 (slightly warm), +2 (warm), and +3 (hot). To procure the data pertaining to room temperature and humidity, a DHT22 device controlled by a Raspberry Pi was used for collection of

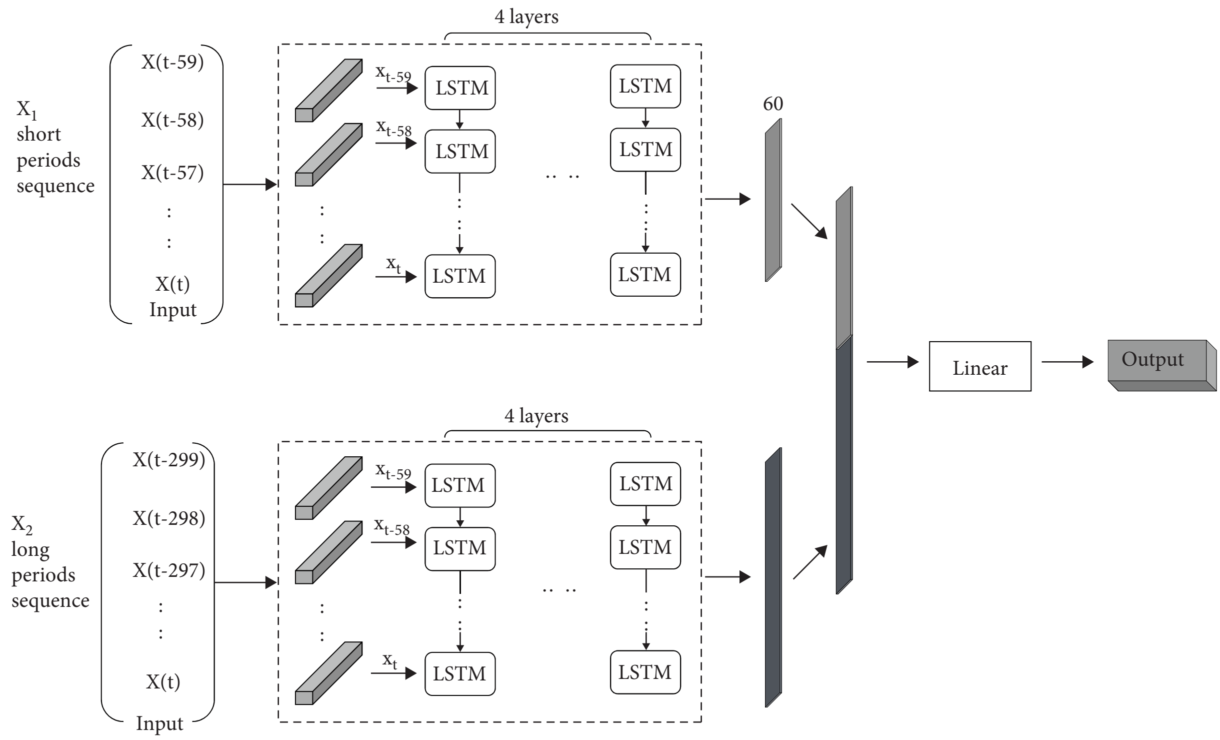

FIGURE 3: Schematic design of the proposed model.

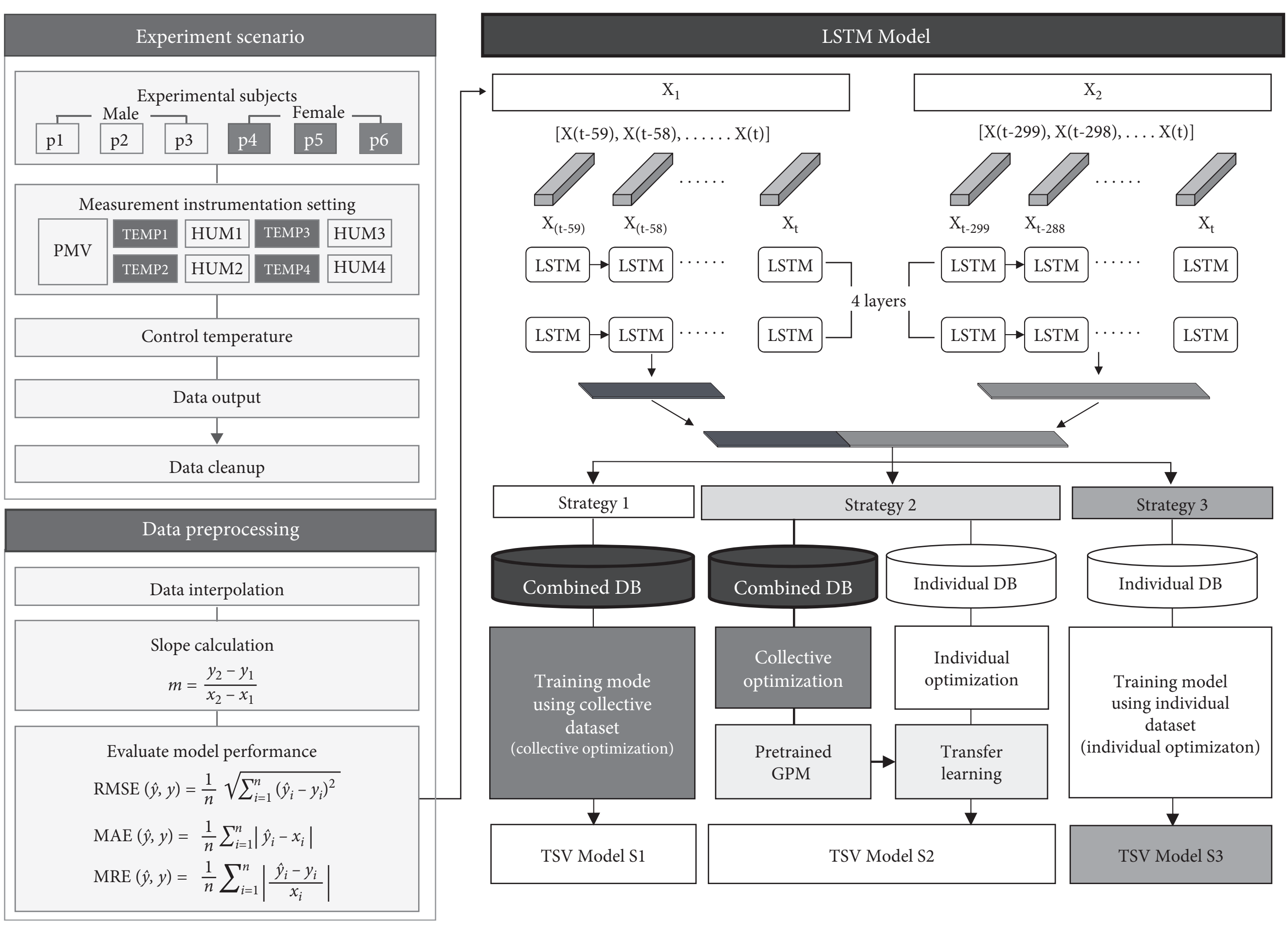

FIGURE 4: Research framework employing LSTM model.

Table 2: Information of measurement instruments.

No.	Instrument	Parameter	Measuring range	Accuracy	Interval	Variables
1	Thermal comfort level recorder	—	−3 to 3	—	5 min	Target value
2	Temperature recorder (DHT22)	Ta	−40 to 80	±0.5	2 s	Indoor environment data
3	Humidity recorder (DHT22)	RH (%)	0–100	±2	2 s	Indoor environment data
4	Temperature recorder (DHT22)	Ta	−40 to 80	±0.5	2 s	Indoor environment data
5	Humidity recorder (DHT22)	RH (%)	0–100	±2	2 s	Indoor environment data
6	Skin thermometer	°C	−40 to 80	±0.5	1 s	Biometric data
7	Skin thermometer	°C	−40 to 80	±0.5	1 s	Biometric data
8	Skin thermometer	°C	−40 to 80	±0.5	1 s	Biometric data
9	Skin thermometer	°C	−40 to 80	±0.5	1 s	Biometric data

Table 3: Equipment information.

No.	Instrument	Parameter	Measuring range	Accuracy	Variables
1	Yanmar Air Conditioner	°C	18–30	—	Temperature
2	HAM-3000BT	RH (%)	−40 to 80	±0.5	Humidty
3	Vornado 633	—	23 m	—	Raumventilator

Table 4: Participant profile.

Participant	Height	Weight	Age
Male 1	172	61	25
Male 2	177	65	23
Male 3	180	79	27
Female 1	163	68	28
Female 2	150	45	22
Female 3	164	59	22

indoor environmental data at 2s intervals. The environmental parameters measured were air temperature (Ta) and relative humidity (RH). For the biometric response data, a flexible sensor was used. The flexible sensor could collect wireless data in units of 1s intervals, and possess good elasticity owing to its Kirigami–Servantine structure [49]. The sensor was attached, and the data were collected keeping in mind the results of a study conducted by Chaudhuri et al. [50], as this location reacts sensitively to the thermal environment and transfers heat to blood vessels faster. The purpose of this study was to determine the correlation between temperature and humidity and to compare thermal comfort objectively as well as subjectively in response to changes in indoor temperature, humidity, living body temperature, and humidity by adjusting the office set temperature within an area of 32 m^2 (3.8 m × 7.8 m). The study subjects included three healthy male and three female college students in their 20s. One female and one male were paired. The participant information is shown in Table 4.

The experiment was conducted for 3 hr each for 2 days for each of the pair, and the temperature of the office radiator was adjusted to 30°C. The experimental scenario is shown in Figure 5. The wireless flexible sensor for recording the temperature and humidity of a living body was attached to the back of the hand in the same manner to all the subjects. The flexible sensor and DHT22 sensor look like Figure 6.

As shown in Figure 7, the air conditioner is located in the center of the chamber, and a humidifier and raumventilator are placed to change temperature and humidity. One sensor was attached to the wall for indoor temperature and humidity measurement was attached 30 cm above the seated subject's head and the other was installed in front of the subject's keyboard. The value of clothing insulation (clo) was set to 0.7 by unifying it with a thin long-sleeved top and jeans.

The energy metabolism (met) was 1.2 which reflected a light task in a sitting position using a computer. Objective thermal comfort values were measured using a Testo 400 device, and subjective thermal comfort values were surveyed by subjects using pop-up programs on computer screens every 5 min.

7. Correlation Analysis

The thermal prediction models proposed in this study were developed on the basis of two types of data: (1) data pertaining to the indoor environment and (2) biometric data of the study subjects. Nine variables were recorded during the experiment (Table 4). T1, H1 (temperature and humidity in front of the keyboard), T2 and H2 (wall temperature and humidity) which reflected environmental factors, and T_R (right hand etmp), H_R (right hand humid), T_L (left hand temp), and H_L (left hand humid) denoted biometric data. The thermal comfort level recorder (subPMV—subjective PMV) was adopted as the output data based on the individual survey data.

The data recorded by the sensors fixed for monitoring the indoor environment and wore by the subjects on their exposed skin were used to train the prediction model as a type of sequence data; thus, collected data were required to

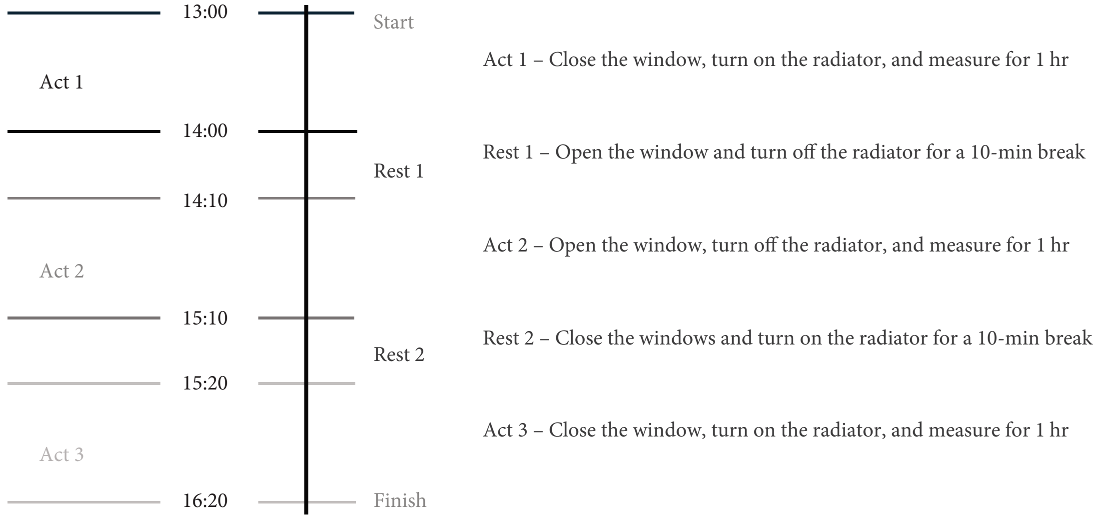

Figure 5: Experimental scenario.

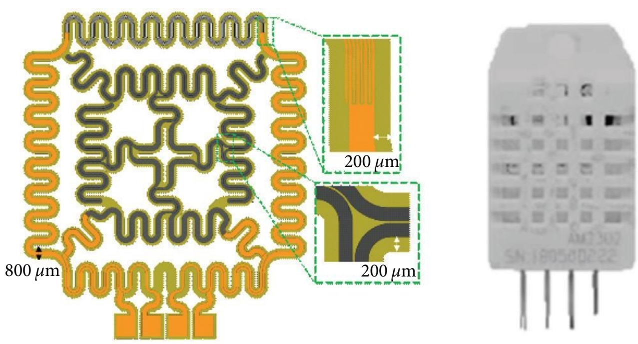

Figure 6: Flexible sensor and DHT 22 sensor.

be filled following a continuous data structure, which was defined as an interval of seconds in this study. Interpolation was used to eliminate the void of the sequence to address the sequence data in units of 1s. Pearson's correlation analysis was used to determine the relationship between subjective thermal comfort and other factors, such as metabolic reactions and indoor environmental variation. The results are listed in Table 5.

Table 5 shows the results of Pearson's correlation analysis between the indoor environment, body temperature, humidity, and subjective PMV examined using IBM SPSS Statistics 24 software. As indicated in the correlation matrix, there existed a significant positive correlation between the indoor temperature and subjective PMV ($P < 0.001$).

Furthermore, the skin temperature was positively correlated to thermal comfort. On the contrary, in the case of humidity, indoor space humidity and the thermal comfort index were found to be negatively correlated; however, the correlation between body humidity and the thermal comfort index was found to be weak. As a result, all the eight variables, except for body humidity, showed a correlation with subjective PMV; therefore, in this study, experiments were conducted taking six variables into account.

8. Experimental Implementation

Several experiments were conducted using three different strategies to evaluate the performance of the proposed architectures. The experimental process is shown in Figure 8. The first strategy was to employ a collective learning method to optimize a model by training an entire dataset simultaneously collected from multiple participants. The second approach was to use a transfer learning method to optimize the separated prediction model using an independent dataset of each participant based on the pretrained weights that were optimized in the first strategy. The final method employed was an individual training method that only used the information of a specific person.

For the conduction of the experiment, we prepared three data groups for training, on the basis of the strategies. For example, the while employing Strategy I the entire first group (63,772 training data) was used. While employing Strategy II, the independent data of participants in the second group (∼10,800 training data per participant for the transfer learning approach) was used to optimize the individual models. However, while employing Strategy III, the training model simultaneously used both the first and second individual data groups (approximately 21,600 training data per participant) for optimization of the independent-oriented prediction model. Each strategy adopted the third dataset group (∼10,800 test data per participant) as a test dataset and measured the performance of all for each model.

To compare the performance of the various architectures in predicting thermal comfort sensation, four models (i.e., FFNN, RNN, LSTM, and multi-LSTM) were adopted in this study. The architecture of the FFNN was a simple neural network consisting of two hidden fully connected layers and an output layer for one target value, which was used to predict the thermal comfort sensation. Meanwhile, the recursive approaches, namely the RNN, LSTM, and multi-LSTM models, were used to address the time-sequential dataset containing thermal comfort sensation. These models

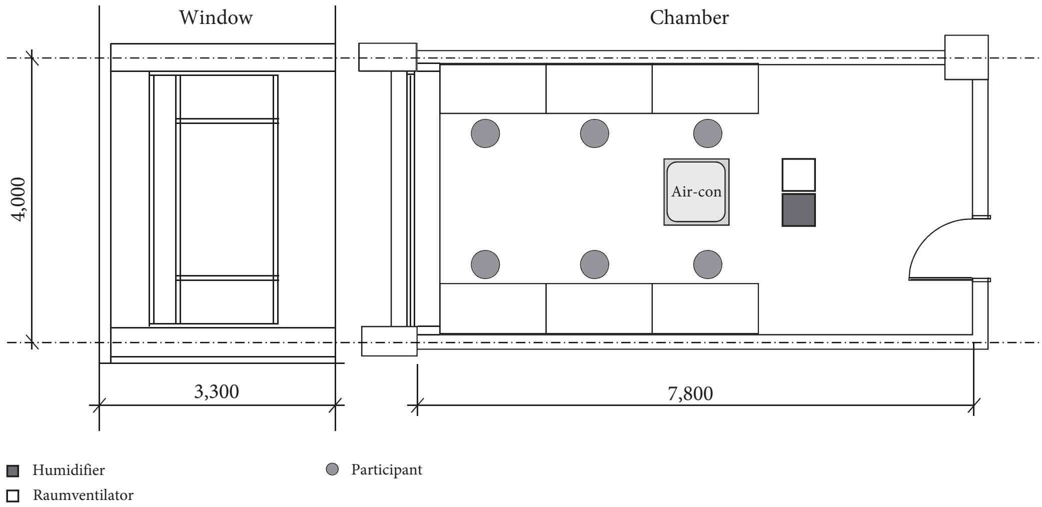

Figure 7: Experiment site.

Table 5: Pearson's correlation analysis.

Variable	subPMV	T1	H1	T2	H2	T_R	H_R	T_L	H_L
subPMV	1.00	—	—	—	—	—	—	—	—
T1	**0.817**	1.00	—	—	—	—	—	—	—
H1	**−0.801**	−0.918	1.00	—	—	—	—	—	—
T2	**0.820**	0.998	−0.911	1.00	—	—	—	—	—
H2	**−0.811**	−0.943	0.979	−0.942	1.00	—	—	—	—
T_R	**0.645**	0.877	−0.811	0.883	−0.842	1.00	—	—	—
H_R	0.096	0.158	−0.089	0.176	−0.126	0.193	1.00	—	—
T_L	**0.692**	0.889	−0.855	0.892	−0.873	0.925	0.136	1.00	—
H_L	0.259	0.234	−0.177	0.220	−0.130	−0.026	−0.026	0.115	1.00

Note. All the correlations have been significant at the 0.01 level (two-tailed). The significance of the bold value indicates that all correlations are significant at the 0.5 level (2-tailed).

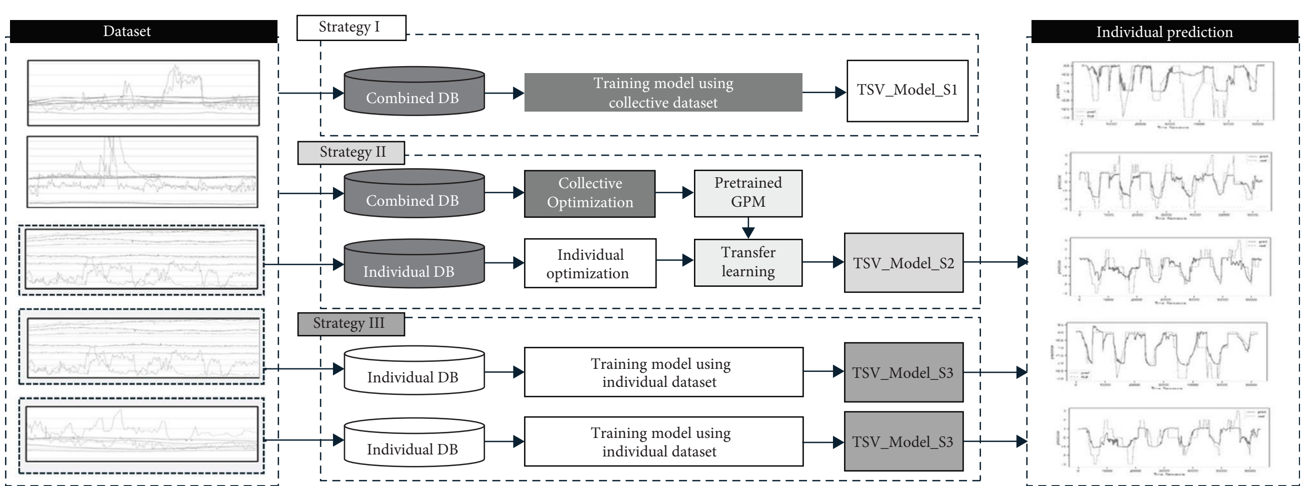

Figure 8: Experimental procedure.

provide the output sequence as one value to predict the thermal comfort sensation at the end of the time steps.

During the model training stage, each input sequence had a length of 300 variables. However, the multi-LSTM model used two datasets having the following lengths: 300-sequence and 60-sequence. To conduct the experiments as per the defined architectures presented above, we considered the six variables as input values by time steps, and the independent PMV as a target value. The model predicted the dependent variable at time step *t*. The network was trained to minimize the cross-entropy loss function of the predicted and true distributions. The other parameters were initialized

Table 6: Overview of performance of the experimental model.

Model name	RMSE			MAE			MRE		
	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
FFNN	1.1677	0.9440	0.2604	1.0228	0.8246	0.2631	0.9510	0.7901	0.2317
RNN	0.9032	0.7678	0.2256	0.7347	0.5606	0.1774	0.6518	0.5277	0.1499
Single-head LSTM	0.9648	0.8028	0.2379	0.7670	0.6035	0.1917	0.6883	0.5209	0.1473
Multi-head LSTM	1.0940	0.8642	**0.2225**	0.7305	0.5552	**0.1620**	0.6673	0.5452	**0.1458**

Strategy 1 (S_1): Training with collective dataset, Strategy 2 (S_2): Training with collective dataset and transfer learning with individual dataset, Strategy 3 (S_3): Training with individual dataset. Values indicated in bold highlight the best performance metrics achieved across the different training strategies for the multi-head LSTM model. The significance of these bolded metrics (RMSE: 0.2225, MAE: 0.1620, MRE: 0.1458) under Strategy 3 indicates the highest efficiency and accuracy in prediction when the model is trained with individual datasets. This underscores the effectiveness of using a more tailored approach in dataset training for improving model performance in these specific metrics.

by random sampling from a uniform distribution on (−0.1, 0.1). The hyperparameters that achieved the best performance on the development set were chosen for the final evaluation. Data were normalized for stable optimization during the training process. The experimental models were trained using the Adam optimizer [51] with a learning rate of 0.0001 for 1,000 epochs. During the training models, we recorded the lowest validation loss in each training epoch to extract the best performance of the experimental models. The experiments were conducted using a Pytorch platform on a workstation with a graphics processing unit (GPU) (GeForce RTX 2090) and a central processing unit (CPU) (Intel Core i9-10900X).

9. Results of the Experiment

9.1. Performance Evaluation Metrics. In this study, the performance of the proposed model using the three metrics, i.e., the root mean squared error (RMSE), the mean absolute error (MAE), and the mean relative error (MRE) were evaluated to ascertain the prediction accuracy; the respective equations are depicted as Equations (12)–(14). The RMSE model is an evaluation method that represents the square root of the variance of the residuals, which indicates the difference between the model's predicted values and the observed values. This model has the advantage of being sensitive to large error values by imposing a large penalty for large error value differences. The MAE model measures the average of the absolute differences between the predicted and the actual observations. The MAE model is intuitively easy to understand. However, it is difficult to use either the RSME model or the MAE model as an absolute index for evaluation because these models vary depending on the size of the target to predicted. Meanwhile, the MRE model determines the magnitude of the MAE value as an absolute value by dividing the difference between the predicted value ($\hat{y}_i$) and the actual value (y_i) by the actual value. Therefore, the MRE model is more suitable for use as an evaluation criterion than the other models.

$$\mathrm{RMSE}\,(\hat{y}, y) = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \tag{12}$$

$$\mathrm{MAE}\,(\hat{y}, y) = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - X_i|, \tag{13}$$

$$\mathrm{MRE}\,(\hat{y}, y) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{x_i}\right|. \tag{14}$$

9.2. Obtained Results. The experimental investigations aimed to evaluate the reliability of the trained bioresponse LSTM for predicting thermal sensation using the adaptive approach while considering the metabolic reactions of the occupants monitored by the flexible sensor. In this study, four different models were used to estimate the thermal comfort based on individual participants. Regarding the diversity of training approaches. The model performance was evaluated using another dataset to validate the trained models. The dataset divided training and validation were divided into two parts. And that the training dataset was evaluated using the validation dataset. Table 6 summarizes the experimental results obtained using the model with the least errors in the training stages, which indicate the average values of each experimenter. Consequently, it was demonstrated that the performance is differed with respect to the architecture and the learning strategy. Furthermore, the proposed model trained using individual data performed the best in these experiments.

The purpose of this study was to demonstrate that a thermal sensation prediction model should consider the characteristics of independent occupants as having different thermal expectations. To determine the contention, the experimental procedure was established using the three approaches. Figure 9 shows the experimental results of the mean relative error of the four different models on the basis of the training approaches.

As shown by the results, the FFNN model had the lowest error rate in Strategy I, and the recurrent-based models provide the lowest error rate in Strategy III. This means that the metabolic fluctuation of the individual participants in response to the environmental changes by time sequence helps to optimize a thermal sensation prediction model by optimizing the independent patterns regarding the thermal expectations. Consequently, we can infer that the recurrent-based network predicts individual thermal sensation more precisely. Moreover, the multihead LSTM model can accurately predict the results specific to individual occupants through a comprehensive and diverse analysis of the patterns.

Figure 10 depicts a bar graph comparing the performance of each strategy in each of the models with respect to each of the respondents. Strategy III, which used only individual data, showed a higher prediction accuracy for all the respondents. This supports the argument that

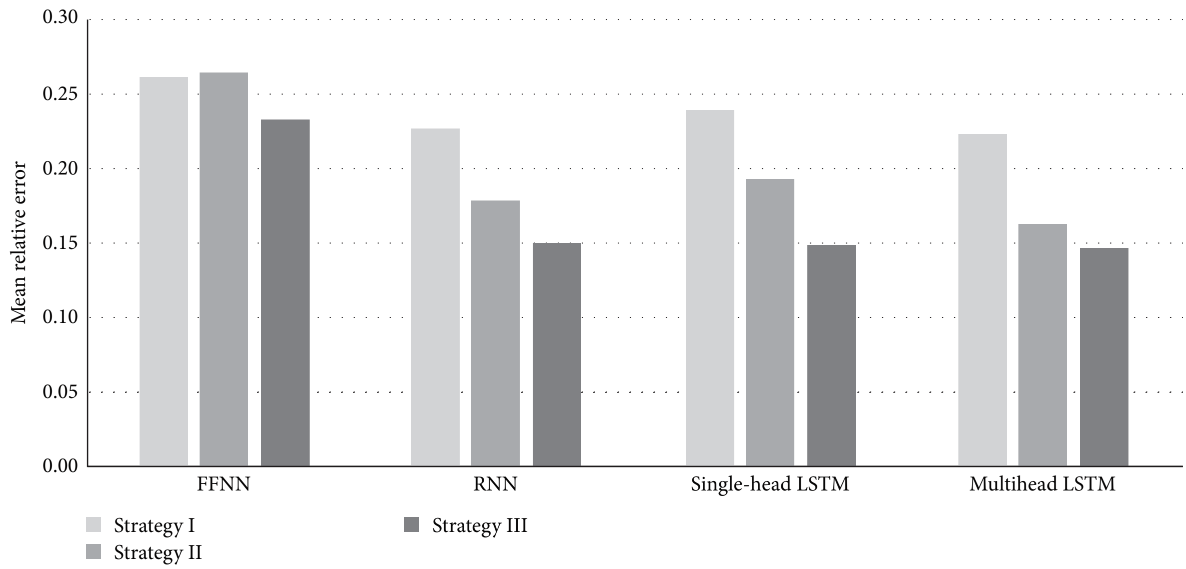

Figure 9: Comparison of performance by strategy according to model.

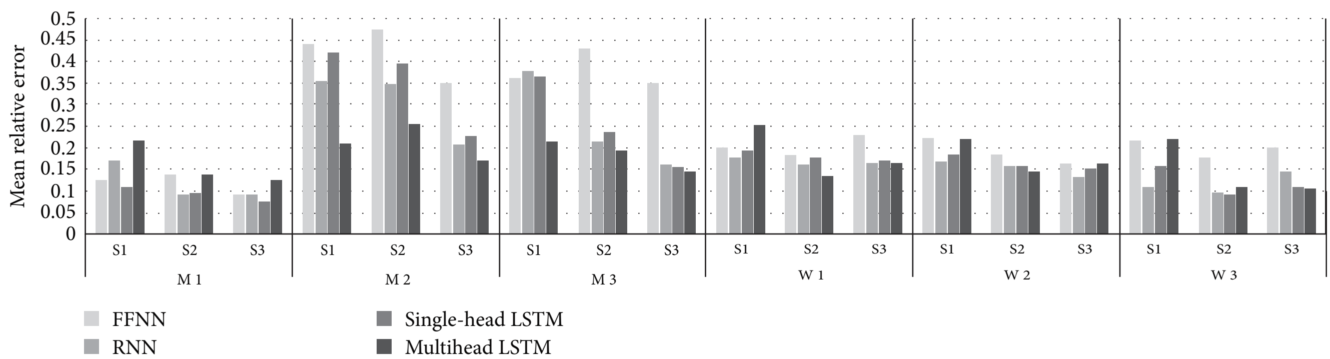

Figure 10: Experimental results by participant.

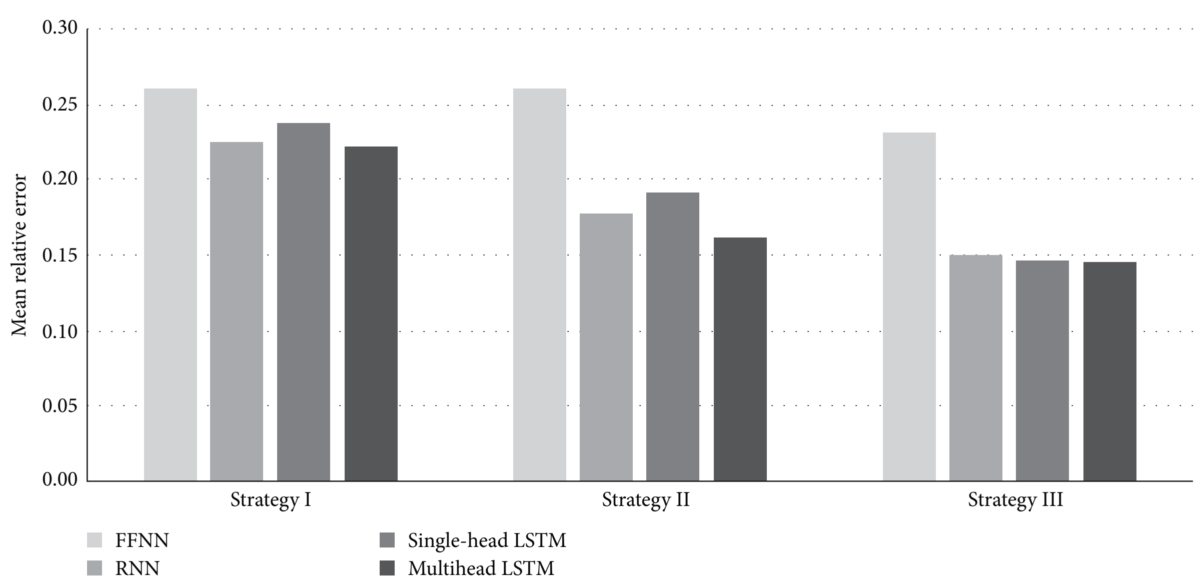

Figure 11: Comparison of the performance of each of the models on applying the three strategies.

the individual responses premised in this study should be considered.

A detailed analysis helped in identification of the differences between the models. All the recurrent-based models except FFNN showed low error rates with respect to application of Strategy III, and the thermal sensation predicted using the recurrent-based model is better correlated better than that calculated with the FFNN model approach. The results showed that the model proposed in this study can better predict the performance. Although the difference in the average performance of the recurrent-based models was somewhat insignificant, the performance of the proposed models was sensitive to various fluctuations in indoor environments through multihead sequential variables (Figure 11).

To sum up, this study determined the accuracy with which the proposed model predicted thermal comfort. The performance was evaluated by training three strategies and four models, and the proposed model trained with individual data displayed the best performance. Consequently, we can infer that circulation-based networks predict individual heat sensations more accurately. We found that the proposed model could improve the individual thermosensory prediction performance.

10. Conclusion

In this study, we investigated the performance of various neural-network-based thermal prediction models in predicting individual thermal comfort. The proposed model was found to outperform other models, using a multihead training approach with data from the indoor environment and physiological responses of individuals. Specifically, the LSTM model was found to be the most effective for predicting individual thermal comfort using sequential data. We compared the FFNN and RNN models in terms of their precision in predicting the thermal comfort of participants exposed to dynamic environments. While the FFNN model has a potential limitation in integrating previous experiences, the RNN model allows the incorporation of contextual information to optimize the prediction model. However, the TSVs of occupants exposed to indoor environments for a long time may be affected by their thermal expectations based on past thermal conditions, limiting the RNN model's ability to learn long-term sequence data. To improve the accuracy of the recurrent network, we adopted the LSTM model, which can address the long-term context of indoor environment data and biometric data. Furthermore, we proposed a multihead LSTM model to address various time sequence information, reflecting participants' responses to changes in the indoor environment. As a result, the LSTM model showed the most effective performance in predicting the thermal comfort of several individuals under diverse environmental conditions, providing results close to the real thermal sensations recorded by the participants.

The experiment conducted in this study was based on a hypothesis that the comfort levels of occupants differed. To validate the optimized models, the test dataset was stabilized as a variable for each experiment, since the data-driven prediction model can have varying prediction performances depending on the training data used. The training model's combined data were classified into three groups of data. In particular, the individual direct training approach proved to be more accurate than the collective training and transfer learning approaches based on the collective training model.

We predicted the thermal comfort of individual occupants using the collective training approach in Strategy I. However, when we tried to predict the thermal comfort sensation of each participant, the performance varied significantly. This was because the diversity of the learning data made it difficult to reflect the characteristics of individual occupants. On the other hand, in Strategy II, the models were trained by optimizing individual data to a pretrained model based on Strategy I, and they showed better performance than Strategy I, although not as good as Strategy III. As a result, we concluded that directly using individual data to optimize the initial algorithm (Strategy III) can lead to more accurate predictions of individual comfort levels. Individual direct training operations were found to be more effective for optimizing the model of individual thermal comfort, as they consider the subjective comfort indicators collected from individuals and their biological response to environmental changes. The potential challenges of this study are twofold. First, the experiments were conducted using intentionally generated indoor environment data in various controlled environments. Second, although approximately 200,000 datasets were collected, they cannot reflect all situations due to being subdivided into several groups. As a result, the model proposed in this study must make use of participant data collected over time. Additionally, the target of this study, which was the sensation to comfort sensation vote, is not a calculated value derived from objective environmental variables, but rather a comfort index recorded by a participant exposed to the experimental environment in 5-min units based on subjective judgment. Therefore, to apply the proposed model in a practical environment in the future, a data-delivering medium that can continuously collect participants' responses is required. Ultimately, individual comfort levels can be determined using a smart device and the indoor temperature and humidity can be adjusted according to the occupants' responses. In the future, the company plans to combine digital twin models with sensors that collect and transmit data in real time to study changes and simulations of temperature and humidity according to residents' reactions.

Acronyms

PMV: Predicted mean vote
Ta: Air temperature
Va: Air velocity
Me: Occupant metabolic rate
LSTM: Long short-term memory
FFNN: Feed forward neural network
MAE: Mean absolute error
HVAC: The heating, ventilation, and air conditioning
SPSS: Statistical package for the social sciences

ASHRAE: American society of heating, refrigerating and air-conditioning engineers
TSV: Thermal sensation vote
Tr: Radiant temperature
Rh: Relative humidity
Cl: Clothing value
RNN: Recurrent neural network
RMSE: Root mean squared error
MRE: Mean relative error.

Data Availability

The data (table and figure) used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (20202020800030, Development of Smart Hybrid Envelope Systems for Zero Energy Buildings through Holistic Performance Test and Evaluation Methods and Fields Verifications).

References

[1] Y. Al Horr, M. Arif, A. Kaushik, A. Mazroei, M. Katafygiotou, and E. Elsarrag, "Occupant productivity and office indoor environment quality: a review of the literature," *Building and Environment*, vol. 105, pp. 369–389, 2016.

[2] K. Lee, S. Lee, and H. Kim, "Accelerating multi-class defect detection of building façades using knowledge distillation of DCNN-based model," *International Journal of Sustainable Building Technology and Urban Development*, vol. 12, no. 2, pp. 80–95, 2021.

[3] B. Salehi, A. H. Ghanbaran, and M. Maerefat, "Intelligent models to predict the indoor thermal sensation and thermal demand in steady state based on occupants' skin temperature," *Building and Environment*, vol. 169, Article ID 106579, 2020.

[4] L. T. Wong, K. W. Mui, and C. T. Cheung, "Bayesian thermal comfort model," *Building and Environment*, vol. 82, pp. 171–179, 2014.

[5] Y. Li, Y. Rezgui, A. Guerriero et al., "Development of an adaptation table to enhance the accuracy of the predicted mean vote model," *Building and Environment*, vol. 168, Article ID 106504, 2021.

[6] B. S. Alotaibi, S. Lo, E. Southwood, and D. Coley, "Evaluating the suitability of standard thermal comfort approaches for hospital patients in air-conditioned environments in hot climates," *Building and Environment*, vol. 169, Article ID 106561, 2020.

[7] P. O. Fanger, *Thermal Comfort: Analysis and Applications in Environmental Engineering*, Danish Technical Press, 1970.

[8] S. Lu, W. Wang, C. Lin, and E. C. Hameen, "Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884," *Building and Environment*, vol. 156, pp. 137–146, 2019.

[9] J. F. Nicol and M. A. Humphreys, "Adaptive thermal comfort and sustainable thermal standards for buildings," *Energy and Buildings*, vol. 34, no. 6, pp. 563–572, 2002.

[10] J. Han, G. Zhang, Q. Zhang et al., "Field study on occupants' thermal comfort and residential thermal environment in a hot-humid climate of China," *Building and Environment*, vol. 42, no. 12, pp. 4043–4050, 2007.

[11] F. Nicol, "Adaptive thermal comfort standards in the hot–humid tropics," *Energy and Buildings*, vol. 36, no. 7, pp. 628–637, 2004.

[12] B. Cao, Y. Zhu, Q. Ouyang, X. Zhou, and L. Huang, "Field study of human thermal comfort and thermal adaptability during the summer and winter in Beijing," *Energy and Buildings*, vol. 43, no. 5, pp. 1051–1056, 2011.

[13] S. Aghniaey, T. M. Lawrence, T. N. Sharpton, S. P. Douglass, T. Oliver, and M. Sutter, "Thermal comfort evaluation in campus classrooms during room temperature adjustment corresponding to demand response," *Building and Environment*, vol. 148, pp. 488–497, 2019.

[14] S.-I. Tanabe, K. Kobayashi, J. Nakano, Y. Ozeki, and M. Konishi, "Evaluation of thermal comfort using combined multi-node thermoregulation (65MN) and radiation models and computational fluid dynamics (CFD)," *Energy and Buildings*, vol. 34, no. 6, pp. 637–646, 2002.

[15] F. Auffenberg, S. Stein, and A. Rogers, "A heating agent using a personalised thermal comfort model to save energy," 2015.

[16] J.-H. Choi and V. Loftness, "Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations," *Building and Environment*, vol. 58, pp. 258–269, 2012.

[17] T. Chaudhuri, D. Zhai, Y. C. Soh, H. Li, and L. Xie, "Thermal comfort prediction using normalized skin temperature in a uniform built environment," *Energy and Buildings*, vol. 159, pp. 426–440, 2018.

[18] A. Aryal and B. Becerik-Gerber, "A comparative study of predicting individual thermal sensation and satisfaction using wrist-worn temperature sensor, thermal camera and ambient temperature sensor," *Building and Environment*, vol. 160, Article ID 106223, 2019.

[19] R. de Dear, J. Xiong, J. Kim, and B. Cao, "A review of adaptive thermal comfort research since 1998," *Energy and Buildings*, vol. 214, Article ID 109893, 2020.

[20] D. Lai, Z. Lian, W. Liu et al., "A comprehensive review of thermal comfort studies in urban open spaces," *Science of the Total Environment*, vol. 742, Article ID 140092, 2020.

[21] R. J. de Dear, E. Arens, Z. Hui, and M. Oguro, "Convective and radiative heat transfer coefficients for individual human body segments," *International Journal of Biometeorology*, vol. 40, no. 3, pp. 141–156, 1997.

[22] E. Halawa and J. van Hoof, "The adaptive approach to thermal comfort: a critical overview," *Energy and Buildings*, vol. 51, pp. 101–110, 2012.

[23] M. Fountain, G. Brager, and R. de Dear, "Expectations of indoor climate control," *Energy and Buildings*, vol. 24, no. 3, pp. 179–182, 1996.

[24] R. Yao, B. Li, and J. Liu, "A theoretical adaptive model of thermal comfort—adaptive predicted mean vote (aPMV)," *Building and Environment*, vol. 44, no. 10, pp. 2089–2096, 2009.

[25] M. Nikolopoulou and K. Steemers, "Thermal comfort and psychological adaptation as a guide for designing urban spaces," *Energy and Buildings*, vol. 35, no. 1, pp. 95–101, 2003.

[26] M. Jowkar, R. de Dear, and J. Brusey, "Influence of long-term thermal history on thermal comfort and preference," *Energy and Buildings*, vol. 210, Article ID 109685, 2020.

[27] J. Xiong, Z. Lian, and H. Zhang, "Physiological response to typical temperature step-changes in winter of China," *Energy and Buildings*, vol. 138, pp. 687–694, 2017.

[28] J.-H. Choi and D. Yeom, "Development of the data-driven thermal satisfaction prediction model as a function of human physiological responses in a built environment," *Building and Environment*, vol. 150, pp. 206–218, 2019.

[29] T. Chaudhuri, Y. C. Soh, H. Li, and L. Xie, "Machine learning based prediction of thermal comfort in buildings of equatorial Singapore," in *IEEE International Conference on Smart Grid and Smart Cities (ICSGSC)*, pp. 72–77, IEEE, 2017.

[30] A. C. Cosma and R. Simha, "Machine learning method for real-time non-invasive prediction of individual thermal preference in transient conditions," *Building and Environment*, vol. 148, pp. 372–383, 2019.

[31] K. Katić, R. Li, and W. Zeiler, "Machine learning algorithms applied to a prediction of personal overall thermal comfort using skin temperatures and occupants' heating behavior," *Applied Ergonomics*, vol. 85, Article ID 103078, 2020.

[32] ANSI/ASHRAE, "ANSI/ASHRAE 55-2013: Thermal Environmental Conditions for Human Occupancy," American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, USA, 2013.

[33] C. Buratti, P. Ricciardi, and M. Vergoni, "HVAC systems testing and check: a simplified model to predict thermal comfort conditions in moderate environments," *Applied Energy*, vol. 104, pp. 117–127, 2013.

[34] J. Xiong, T. Ma, Z. Lian, and R. de Dear, "Perceptual and physiological responses of elderly subjects to moderate temperatures," *Building and Environment*, vol. 156, pp. 117–122, 2019.

[35] A. Ghahramani, G. Castro, B. Becerik-Gerber, and X. Yu, "Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort," *Building and Environment*, vol. 109, pp. 1–11, 2016.

[36] K. Katić, R. Li, J. Verhaart, and W. Zeiler, "Neural network based predictive control of personalized heating systems," *Energy and Buildings*, vol. 174, pp. 199–213, 2018.

[37] M. Abdulgader and F. Lashhab, "Energy-efficient thermal comfort control in smart buildings," in *IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 22–26, IEEE, 2021.

[38] J.-M. Yeom, R. C. Deo, J. F. Adamowski, S. Park, and C.-S. Lee, "Spatial mapping of short-term solar radiation prediction incorporating geostationary satellite images coupled with deep convolutional LSTM networks for South Korea," *Environmental Research Letters*, vol. 15, no. 9, Article ID 094025, 2020.

[39] C. Huizenga, Z. Hui, and E. Arens, "A model of human physiology and comfort for assessing complex thermal environments," *Building and Environment*, vol. 36, no. 6, pp. 691–699, 2001.

[40] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: the state of the art," *International Journal of Forecasting*, vol. 14, no. 1, pp. 35–62, 1998.

[41] S. Y. Chan and C. K. Chau, "Development of artificial neural network models for predicting thermal comfort evaluation in urban parks in summer and winter," *Building and Environment*, vol. 164, Article ID 106364, 2019.

[42] U. Yolcu, E. Egrioglu, and C. H. Aladag, "A new linear & nonlinear artificial neural network model for time series forecasting," *Decision Support Systems*, vol. 54, no. 3, pp. 1340–1347, 2013.

[43] X. Dai, J. Liu, X. Zhang, and W. Chen, "An artificial neural network model using outdoor environmental parameters and residential building characteristics for predicting the nighttime natural ventilation effect," *Building and Environment*, vol. 159, Article ID 106139, 2019.

[44] Z. C. Lipton, J. Berkowitz, and C. Elkan, "A critical review of recurrent neural networks for sequence learning," arXiv preprint arXiv: 1506.00019, 2015.

[45] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training recurrent neural networks," in *International Conference on Machine Learning*, pp. 1310–1318, Pmlr, 2013.

[46] S. Hochreiter and J. C. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[47] S. O. Arik, H. Jun, and G. Diamos, "Fast spectrogram inversion using multi-head convolutional neural networks," *IEEE Signal Processing Letters*, vol. 26, no. 1, pp. 94–98, 2019.

[48] P. Liu, X. Qiu, X. Chen, S. Wu, and X.-J. Huang, "Multi-timescale long short-term memory neural network for modelling sentences and documents," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 2326–2335, Association for Computational Linguistics, Lisbon, Portugal, 2015.

[49] M. Naqi, S. Lee, H-Jun Kwon et al., "A fully integrated flexible heterogeneous temperature and humidity sensor-based occupancy detection device for smart office applications," *Advanced Materials Technologies*, vol. 4, no. 12, Article ID 1900619, 2019.

[50] T. Chaudhuri, D. Zhai, Y. C. Soh, H. Li, and L. Xie, "Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology," *Energy and Buildings*, vol. 166, pp. 391–406, 2018.

[51] Z. Zhang, "Improved adam optimizer for deep neural networks," in *IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)*, pp. 1-2, IEEE, 2018.