This is the accepted version of the publication Lee C, Tan J, Tan JJ, Tang HT, Yu WS, Lam NYK. Integrating artificial intelligence for optimal thermal comfort: A design approach for electric heating textiles aligned with user preferences. Textile Research Journal. 2024;0(0). Copyright © 2024 The Author(s). DOI: 10.1177/00405175241275620.

# Integrating Artificial Intelligence for Optimal Thermal Comfort: A Design Approach for Electric Heating Textiles Aligned with User Preferences

## Abstract

Human thermal comfort, crucial for well-being and productivity, is often improved by personal comfort systems that offer tailored control over environmental conditions while promoting energy efficiency. Previous studies have explored various textile technologies in thermoregulation systems according to user preferences. However, limited research has focused on temperature prediction by artificial intelligence (AI) to maximize thermal comfort for varied users. This study proposes a design approach to optimize thermal comfort in electric heating textiles using AI, considering user preferences related to age and gender differences. A fuzzy logic model is established as a proof of concept for temperature regulation by varying ambient temperature, followed by developing an artificial neural network (ANN) model to predict the optimal temperature for maximum comfort. Subsequently, a smart electric heating jacket is fabricated to assess preferred heating temperatures among 50 subjects with varying ages and genders. Results from the ANN model show promising temperature prediction, while subject tests reveal significant differences in skin temperatures based on gender. This emphasizes the need for AI-based heating e-textiles to accommodate diverse user needs. The study's findings are expected to contribute to intelligent temperature regulation in thermal textiles and wearables, benefitting both the industry and consumers through customized heating products.

## Keywords

Heating textile, intelligent textile, thermal comfort, personal comfort system, artificial neural network

## Introduction

Thermal comfort constitutes a complex human experience influenced by the thermal conditions of both the skin and the body's core.[1] Research indicates significant regional differences in thermal comfort preferences across the body's surface, with particular areas at the back upper torso, abdomen, and feet showing a pronounced preference for warmer temperatures.[2] Personal Comfort Systems (PCSs) plays a crucial role in empowering individuals to customize their immediate environment according to their comfort preferences, thus enhancing overall satisfaction with ambient conditions. Furthermore, it offers a practical approach to improving energy savings by preventing overheating and optimizing energy use. Research has shown that a substantial amount of energy is wasted on maintaining the temperature of unoccupied spaces and inanimate objects inside buildings by using conventional heating, ventilation, and air conditioning (HVAC) systems consume significant energy due to their uniform regulation of indoor air temperatures, rather than prioritizing human comfort.[3-5] A research has shown that heating chairs can save up to 71.0% of total energy (at 14°C) when combined with leg-warmers. Another research indicates that smart passive and active thermoregulatory textiles have the potential to widen the comfortable temperature range by up to 6.5°C and 14°C, respectively, with minimal or zero energy consumption.[6] In contrast to centralized space heating and cooling systems, smart thermoregulatory textiles significantly reduce the volume of heating or cooling required and expand their application to various outdoor settings. Despite advancements, challenges related to thermal comfort persist in artificial environments, impacting daily life and activities.[7] Measurement of thermal comfort typically involves assessing thermal sensation (TS) and comfort sensation (CS).[8] The common evaluation method to assess the effectiveness of heating textiles is to compare thermal comfort between experimental groups (heating textiles with power on) and control groups (heating textiles with power off).[9-14] However, previous studies only demonstrate the necessity of heating and warming the human body in cold environments to maintain satisfactory TS and CS without further understanding of how to develop heating textiles that achieve maximum thermal comfort based on user preferences.

Electric heating textile products are typically employ either direct current (DC) voltage regulation or pulse duty ratio regulation methods to control heating intensity.[15] Heating principle and temperature control system of electric heating textiles could be explained by the Joule heating effect (Ohm's Law). When the energy of an electric current flows through resistance by using metallic yarn as the bus bar and a low resistance silver or copper-coated polymeric yarn as a heating material,[16-18] heat will be emitted and provide a warming effect. The expression for Ohm's law is:

$$\mathrm{P} = \mathrm{VI} = I^2R \tag{1}$$

where P, V, I and R representing power, voltage, current and resistance respectively. Commercial thermal conductive textile products,[19, 20] have a wide range of applications, including outdoor apparel, domestic thermal products and healthcare and medical treatments in which beneficial in joint pain relief, muscle spasms relaxation and recovery enhancement via improving blood circulation.[21] However, exposure to excessive heat can lead to various health and psychological issues, resulting in decreased work productivity and dysfunction of vital organs.[21-26] Typical textile heaters, which warm to 40-45 °C within 20 minutes, can sometimes cause severe contact burns, especially when used without medical guidance.[21, 23] The risk is higher for the elderly, diabetics, and individuals with dysesthesia due to poor thermal perception.[25] Recent products with thermostats and timers help minimize overheating but have limitations in precision and even heating distribution. Timers may also fail during extended use, like overnight. Thus, a safer approach is intelligent temperature regulation to balance ambient and body temperatures. Ensuring optimal thermal conditions is essential wherever environmental changes occur. Several smart electric heating textiles were invented for real-time temperature control according to user preferences and needs. Bluetooth connections are commonly included in the user interface to allow users to adjust the heating temperature via apps on their smartphone for controlling the heating fabric panels wirelessly.[5, 20, 23, 27-30] Temperature data could be collected and recorded at one-second intervals by an Arduino microprocessor.[31] Essential components of the thermoregulation system comprise temperature and humidity sensors, power control, measurement and voltage regulation electronics, and batteries.[15, 30] Further research has explored smart heating textiles, such as sensor shirts, integrating skin conductivity and respiration sensors for analytical purposes.[30] Regarding temperature control, the most common methods are On/Off control and Proportional-Integral-Derivative (PID) control.[32-34] On/Off control establishes a threshold and regulates the temperature of the clothing microclimate closest to the skin. PID controller is a control loop mechanism with feedback engagement and is widely used in industrial applications.[27, 35] A PID controller allows the error value to be calculated continuously to predict the output value.

Compared to the PID controller, fuzzy logic (FL) based control offers a more accessible and efficient way of tackling the identified challenges.[36] In the case of electric heating textiles, which involve complex interactions between the textile material, the environment, and the user's body, FL can provide a flexible and adaptable control strategy in which is commonly applied in controlling heating systems to achieve a comfortable sensation in a warm environment by maintaining room temperature within the required temperature range.[27, 37] It is a form of many-valued logic that resembles human reasoning.[38, 39] Generally, FL controller structure includes three stages: fuzzification, inference, and defuzzification.[40, 41] Previous research shows several fuzzy controllers applied in textile technology.[36, 42, 43] The FL mathematical model controlling the heating system includes specifying the input (ambient temperature) and output (heater) values.[44] The FL control system operates a heater so that the heater automatically adjusts the temperature upwards or downwards depending on the ambient temperature. FL indeed provides a simpler framework for modeling relationships, particularly in systems where inputs and outputs are not precisely defined.[45, 46] However, it may not handle complex data as effectively as artificial neural networks (ANNs), which are known for their ability to capture complex, nonlinear relationships and adapt to new information.[47] ANNs are indeed versatile in prediction and can be used to model diverse user preferences, making them suitable for optimizing thermal comfort across different demographic groups. In ANN, there is a feed-forward neural network in which the inputs are processed only in the forward direction. [48] There are three types of functions in ANN: (1) input nodes, (2) hidden nodes, and (3) output nodes.[49-51] The below equation shows the typical architecture of ANN:

$$h_i = \sigma\left(\sum_{j=1}^{N} V_{ij}x_j + T_i^{hid}\right) \tag{2}$$

where $h_i$ is the output, $\sigma(\,)$ is the activation function, $N$ is the number of input nodes, $V_{ij}$ is the weight, $x_j$ is the input to the input nodes, $T_i^{hid}$ is the threshold terms of the hidden nodes. The neurons are typically organized into multiple hidden layers, especially in deep learning,[52, 53] which refers to multi-layer perceptron (MLP) as it possesses three or more layers of perceptrons and the data would pass in one-way direction from (1) input layer, and then to (2) hidden layers, and finally to (3) output layer.[54] Within the textile industry, artificial intelligence (AI) has found successful application in fabric inspection and the enhancement of production systems through neural networks and artificial vision.[36, 55] Researchers are exploring numerous compatible applications for integrating AI into smart textiles in the future. Heating textile technologies mentioned above were predominantly outfitted with sensors to regulate temperature based on fluctuations in ambient parameters or provide users with autonomous temperature control, however, with limited regard for temperature prediction for optimal thermal comfort. Despite advancements, challenges related to thermal comfort persist in artificial environments, impacting daily life and activities. Previous studies focused on app development and automatic on/off controls to regulate the temperature of heating textiles. While these advancements provided convenience, they failed to address the risk of overheating and neglected the need for optimal thermal comfort customization based on gender and age variations. The integration of AI technology offers a promising solution, enabling smart heating textiles to achieve optimal thermal comfort tailored to individual user preferences. Additionally, they can result in significant energy savings by preventing overheating and optimizing energy use. This is achieved by targeting specific areas that need heating and dynamically adjusting heating levels based on real-time data. This improved energy efficiency can lead to lower operational costs over time.

This study proposes a design framework to integrate AI for achieving optimal thermal comfort in electric heating textiles, tailored to user preferences. Illustrated in Figure 1, this framework comprised multiple phases. The initial step involved establishing a temperature regulation system utilizing FL to govern heating e-textiles through if-then rules in response to ambient changes. This preliminary phase aimed to validate the efficacy of temperature regulation on heating e-textiles. During the technological development stage, an ANN model was trained, with the option to employ either Logistic (Sigmoid) or Rectified Linear Activation (ReLU) activation function, to predict optimal ambient temperatures conducive to achieving maximum human thermal comfort. Utilizing input variables derived from an open-source dataset, the ANN model aimed to optimize thermal comfort levels by determining the ideal interior ambient temperature for individuals of various ages and genders. Following the confirmation of compatibility among electronic modules, controllers, and temperature sensors for temperature control in heating e-textiles, the subsequent phase focused on the fabrication of a smart heating e-textile integrated with Bluetooth temperature control to modulate power consumption for heat generation. The final phase involved the development of a prototype smart heating e-textile in the form of a jacket, followed by wearer trials. These trials investigated heating temperatures required to achieve maximum thermal comfort based on user preferences and compared the results with those generated by the ANN model. The results of the study are anticipated to advance intelligent temperature control in thermal textiles and wearables, providing tailored heating solutions that benefit both industry stakeholders and consumers.

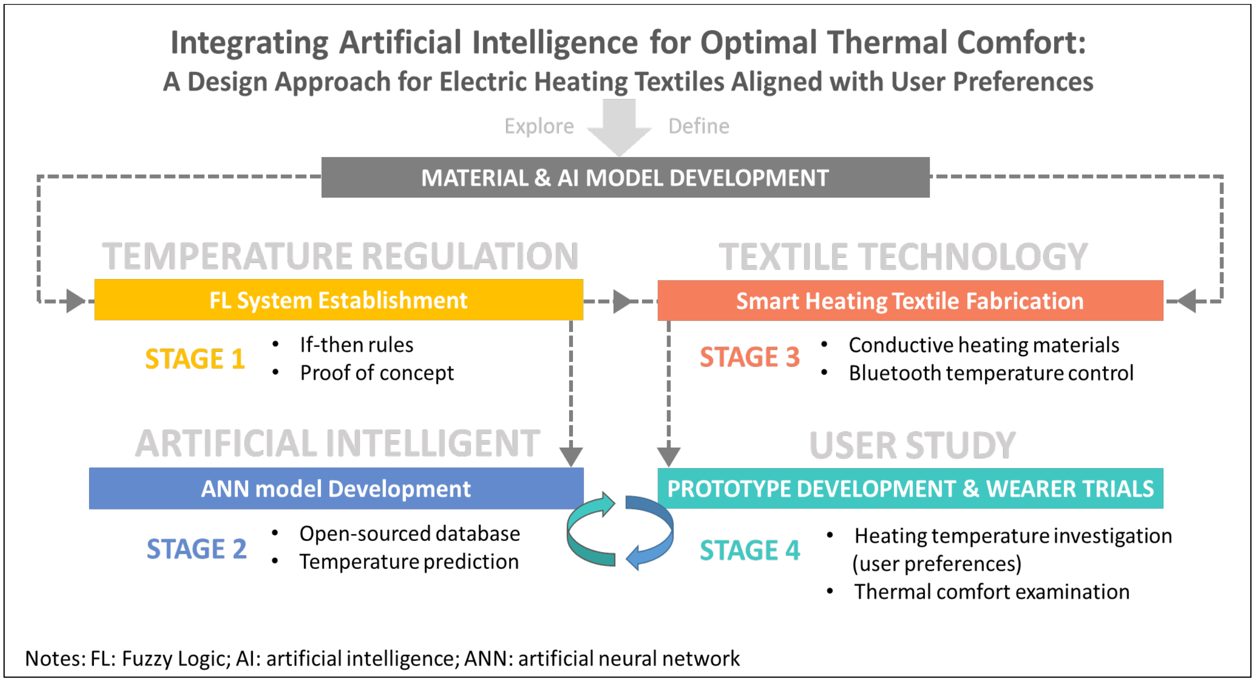


**Figure 1.** Process for a design approach for electric heating textiles aligned with user preferences by integrating AI for optimal thermal comfort

## Methodology

*FL system establishment for temperature regulation.* The FL controller system consists of an adjustable power source, conductive heating fabric, and a microcontroller equipped with a temperature sensor module, as depicted in Figure 2a. MATLAB, along with the FL toolbox, was used to design and simulate the temperature regulation system within the heater controller. The FL model's parameters primarily included the input membership function, ambient temperature, and the output value representing the heater power output, as illustrated in Figure 2b. To simulate a controllable indoor environment with cool conditions during testing, input membership functions for ambient temperature (i.e., cold, warm, and hot) ranged from 15 to 20°C, while output membership functions for heater power output (i.e., cooling, warming, and heating) ranged from 0 to 100%, as shown in Figure 2c. Within the FL controller system, ambient temperature served as the input membership function during the fuzzification stage, while the output value during the defuzzification stage determined the electric power supplied to the conductive heating fabric. A set of linguistic IF–THEN rules, as depicted in Figure 2d, was formulated to describe the relationship between the heater's power and ambient temperature during the inference stage.

Accordingly, as ambient temperature fluctuated, the heating e-textile responded at a specific heating level. Various combinations of rules were simulated, as illustrated in Figure 2e, with corresponding power output values for different ambient temperature conditions. Figure S1 (Supporting Information) summarized the input and output values within the IF–THEN rules of the controller system. The output variable development within the FIS MATLAB was subsequently converted into the C programming language and implemented in Arduino. The simulation results, presented in Figure 2f, demonstrated the functionality of the system. As the parameters of the input value could only be set as integer numbers, the values of the input membership function were rounded up to the nearest integer for the Arduino program. Upon connecting the Arduino board with a power supply and fabric heater, the power output could be automatically triggered and controlled according to the input of ambient temperature by the FL decision. If ambient temperature exceeded 20°C, power was cut off to cool the heater, while heating continued at 100% if Ta fell below 15°C. The values set for Ta within the IF–THEN rules could be adjusted based on actual circumstances or experimental testing results.

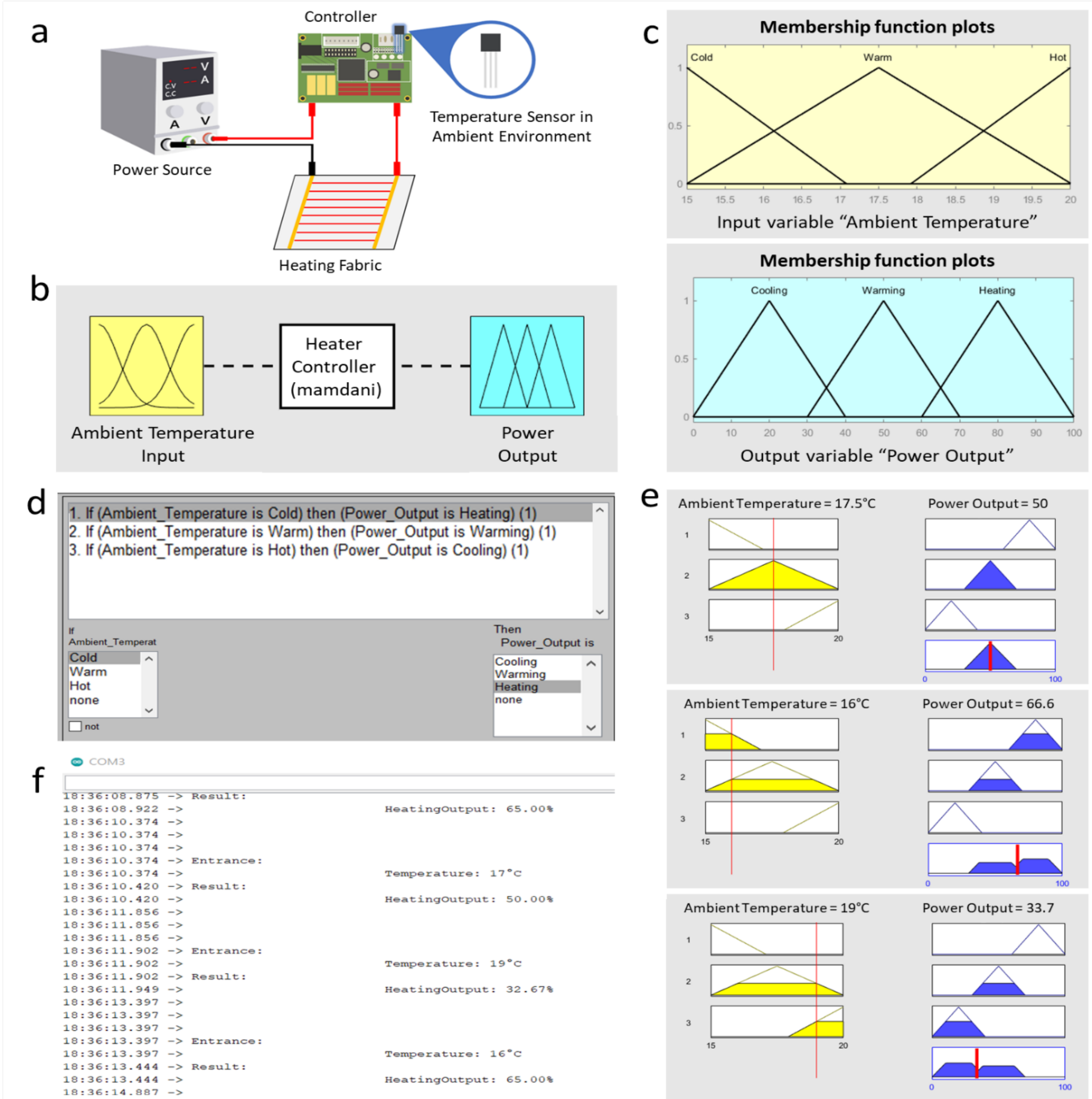


**Figure 2.** FL system establishment: (a) Temperature regulation system design for electric heating textile. (b) FL design of heater controller. (c) Membership functions of the fuzzy controller input and output. (d) IF–THEN rules in FL of heater controller. (e) Different combination of FL in rule viewer. (f) Simulation result in Arduino.

*ANN model development for temperature prediction.*

The training dataset for the ANN models was sourced from the ASHRAE worldwide database of thermal comfort field measurements.[56] During the construction of the ANN models, a subset comprising 3806 datasets, characterized by the highest level of TS acceptability (rated at 6), was extracted. Establishing associations between input variables encompassing age, gender, relative humidity (%RH), air velocity (m/s), and the target output variable—the optimal ambient temperature (°C)—was fundamental in constructing the ANN models, as depicted in Figure 3a. To ensure the accuracy and reliability of the ANN model prediction, two hidden layers were incorporated into this ANN architecture to enhance structural complexity with a substantial number of neurons. This dataset was utilized for training purposes and for collecting weighted matrices within the framework of the ANN, as illustrated in Figure 3b to 3d showing the input and output variables. The computational aspect of this process was facilitated through the utilization of Python's Scikit-Learn library.[57] Renowned for its extensive and proficient capabilities, this software resource was particularly significant in the realm of statistical modeling and machine learning, notably in the predictive phase of data analysis. The comparison between ANN outputs from predictive models was conducted through the utilization of the sigmoid and ReLU activation functions. Mean Squared Error (MSE) was employed as the chosen error metric, serving as a valuable tool for evaluating the accuracy of predictions generated by loss functions during the training of ANNs. This metric quantified the extent of deviation within the statistical model, with an increase in model error corresponding to a concurrent increase in the MSE value. In this study, the configuration for the sigmoid or ReLU activation function included the number of neurons in hidden layers 1 and 2, with the configuration yielding the lowest MSE value being applied in further analysis. The computation of MSE is represented in Equation 3.

$$MSE = \frac{\sum(y_i - \hat{y}_i)^2}{n} \tag{3}$$

where $\hat{y}_i$ is the corresponding predicted value, $y_i$ is the $i^{th}$ observed value and $n$ is the number of observations.

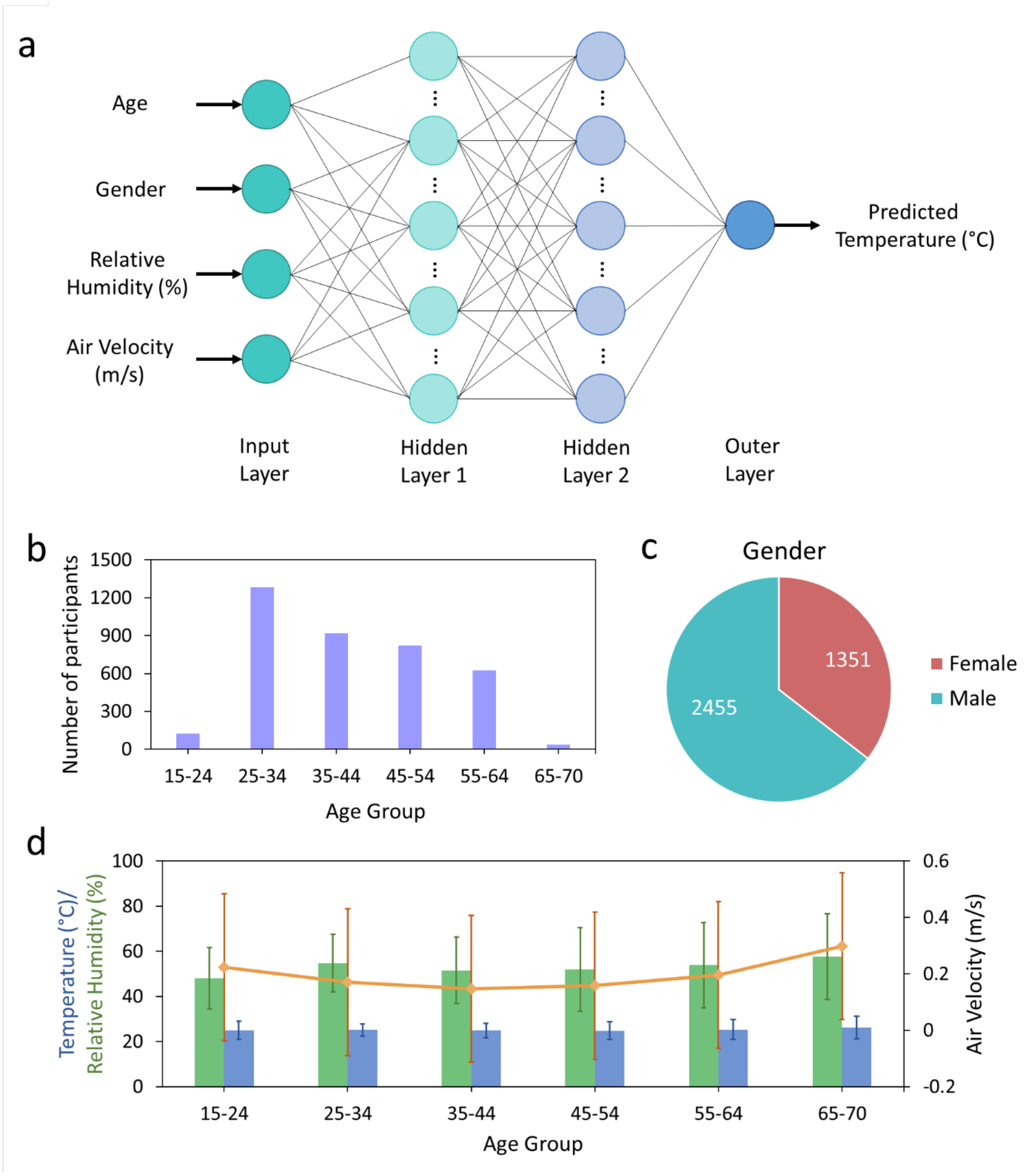


**Figure 3.** ANN Model Development: (a) Structure of the ANN model for temperature prediction. (b) The dataset extracted from the ASHRAE worldwide database for ANN training in this study included input variables such as the number of participants categorized into six age groups, (c) gender differences, (d) relative humidity, and air velocity, with the output variable being temperature.

*Conductive heating textile fabrication.* The heating e-textile in this study was developed using weaving and embroidery processes, adhering to Ohm's Law. In the weaving process, 40/2s Black cotton yarn was purchased from the market to serve as the insulating passive yarn in the warp direction. Meanwhile, 40DA silver-coated yarn with a resistance of 32Ω/cm was purchased from Shandong Boyin Surface Functional Materials Co., Ltd., China, and was utilized in the weft direction as the conductive heating yarn. Additionally, another 200D silver-coated yarn with a resistance of 2.54Ω/cm was purchased from Thinger Textile Co., Ltd., China, and was embroidered onto the fabric surface in the warp direction to act as a pair of electrodes post-weaving. SEM images of these two types of silver-coated yarns for heating and electrodes are depicted in Figure 4a. A rapier sample loom (CCI/ SL7900) employing dobby shedding motion at a speed of 25 rpm was utilized for weaving, while a TAJIMA -SAI- embroidery machine was employed for embroidering the pair of electrodes onto the heating fabric, as illustrated in Figures 4b and 4c. The weaving structure of the heating e-textile was fabricated in a double-sided diamond twill (Figure 4d). The warp and weft densities were 72 ends/inch and 80 ends/inch, respectively, to increase the number of conductive heating yarns and thereby enhance heating efficiency. A diamond pattern was applied due to its symmetry along the vertical and horizontal axes, ensuring even distribution in each small repeat sector. Figure 4e displays images and thermal images of the heating e-textile. Upon connecting the pair of electrodes to the embroidered conductive parts, the central heating segment was able to reach an average temperature of 52.5°C within 1 minute, with a power consumption of 12V and 1.18A.

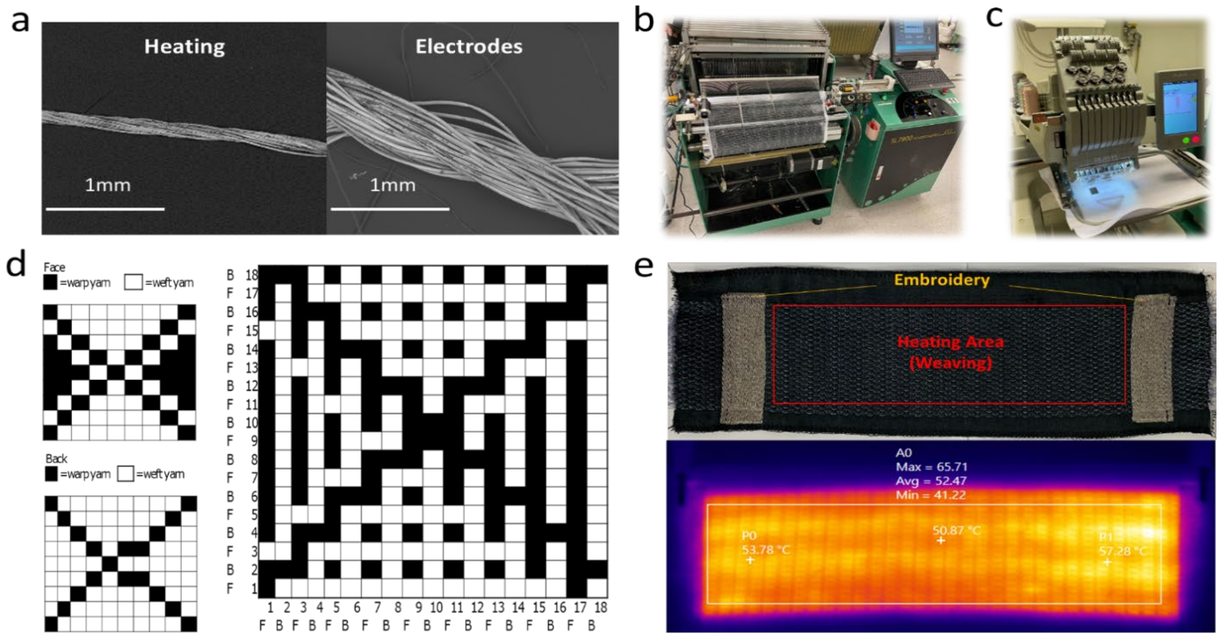


**Figure 4.** Smart Heating Textile Fabrication: (a) Scanning electron microscopy (SEM) images of silver-coated yarns for heating and electrodes. (b) Weaving and (c) embroidery machines applied in fabrication. (d) Structure diagram of weaving structure of heating e-textile. (e) Image and thermal image of heating e-textile.

*Fabrication of smart heating jacket.* Controllers (ESP-32) equipped with wireless Bluetooth connectivity were utilized in both the electric heating textile and ambient sensors, enabling real-time data collection of ambient temperature, relative humidity, air velocity, and heating temperature on the heating textile to be transmitted to a computer (PC) for temperature control and monitoring (Figure 5a). Electronic module sensors, including ambient temperature and relative humidity (BME680) with smallest resolution as 20bit and accuracy ±1.0°C, air velocity (FS3000), and thermocouple (MAX6675), were purchased from Adafruit Industries., Ltd., US, SparkFun Electronics., Ltd., US, and Maxim Integrated Products, Inc., US, respectively and were integrated into the system (Figure 5b). For wearer trial tests, the heating e-textile was integrated into a customized jacket with a pocket housing the ambient sensor system, forming a smart heating jacket (Figures 5c and 5d). Research indicates that the upper back torso is a significant region with distinct thermal comfort preferences across the body's surface, showing a strong preference for warmer temperatures.[8] To explore the feasibility of using a small heating area to achieve maximum user comfort and energy savings, a heating textile with a heating area measuring 6cm in length and

20cm in width was positioned on the upper back torso. The jacket primarily comprised polyester fabric with a thickness of 0.193mm, and its size was tailored to fit an international male M size, thus accommodating a broader spectrum of subjects. A screen capture image on the PC illustrated real-time wireless heating temperature control and monitoring, as well as ambient temperature, relative humidity, and air velocity via Bluetooth (Figure 5e). Figure 5f showed the controlled environment set-up for wearer trial.

*Wearer trials.* 50 healthy subjects aged 18 to 89, comprising 14 males and 36 females, were recruited for the study via posters at The Hong Kong Polytechnic University. Table S1 (Supporting Information) showed the demographic information. Participants provided signed informed consent after understanding the study's purpose and procedures, and they underwent a pretest. Ethical approval was obtained by the Ethical Committee of The Hong Kong Polytechnic University (HSEARS20200123003). Physical examinations and questionnaires were conducted to evaluate the heating temperature of the smart heating jacket to achieve maximum thermal comfort across different ages and genders. Subjects were forbidden to drink alcohol and instructed to refrain from extensive exercise for 8 hours before the experiment.

Regarding subjective TS and CS evaluation, the jacket's heating temperature was controlled to increase by 1°C per minute, starting from 40°C. Subjective evaluations of TS and CS were performed every minute after each 1°C increase. Participants were asked, "Which item describes your current state of thermal sensation and comfort sensation best?" after the heating temperature increased by 1°C. The evaluations were conducted using a Semantic Differential Scale for both TS (-3: cold, -2: cool, -1: slightly cool, 0: neutral, +1: slightly warm, +2: warm, +3: hot) and CS (-3: very uncomfortable, -2: uncomfortable, -1: slightly uncomfortable, 0: neutral, +1: slightly comfortable, +2: comfortable, +3: very comfortable).

In terms of the experimental protocol, subjects were required to wear the smart heating jacket and remain seated inside a cold environmental chamber under two conditions: high wind (21°C, 60%RH, 3m/s) and cold (17°C, 70%RH, 0m/s). A chair for the subject to sit on, an electronic fan, an air conditioner, a portable electronic thermometer and hygrometer purchased from Xiaomi, Inc., China, and an anemometer purchased from Delixi, Ltd., China, were included in the controlled chamber. Initially, upon entering the environmental chamber, the heating power was switched off, and the subject sat on a chair for 15 minutes before commencing the wearer trial test. After the 15-

minute period, the subject remained seated, the heating power was activated, and the heating temperature was regulated to increase by 1°C per minute, starting from 40°C. Subjects were instructed to complete questionnaires regarding TS and CS until achieving a CS rating of +3, indicating maximum thermal comfort. The corresponding heating temperature required to achieve maximum thermal comfort was recorded and evaluated. Open-ended questions pertaining to material improvements, fitting, and applications were included and summarized to enhance usability.

IBM Statistical Product and Service Solutions (SPSS) Statistics 26 was utilized for statistical analysis to assess the effectiveness of the heating jacket in maintaining body warmth to achieve maximum thermal comfort. SPSS offers advanced statistical procedures that are useful for building and validating predictive models. The effectiveness of the heating jacket in maintaining warmth and achieving maximum thermal comfort can be validated using paired t-tests, comparing results from before (pre-test) and after (post-test) applying the heating jacket. The following assumptions need to be met: subjects must be independent of one another, the dependent variable must be continuous, approximately normally distributed, and free of outliers. Results from SPSS analysis provide a p-value, indicating whether the correlation is statistically significantly different from zero. If the p-value is less than 0.05, the null hypothesis that the correlation is zero can be rejected. The effect size for a paired-samples t-test can be calculated by dividing the mean difference by the standard deviation of the difference. 95% confidence interval (CI) is constructed for the mean difference. The calculating the t-score in a paired t-test is represented in Equation 4.

$$t = \frac{\bar{d}}{\frac{s_d}{\sqrt{n}}} \tag{4}$$

Where $\bar{d}$ is the mean of the difference scores, $s_d$ is the standard deviation of the difference scores and $n$ is the number of pairs of observations.

Additionally, SPSS was employed to determine the statistical significance of higher mean skin temperature and temperature preferences across different age groups and genders. The analysis was conducted using independent (two-paired) sample t-tests and one-way ANOVA, with participants divided into several groups for comparison. The assumptions for independent sample t-tests included numeric data, independent observations, equal chance of selection for each individual within the population, normally distributed sample means, and equal variances between groups. The effect size is calculated using Cohen's d, where the mean difference is standardized.

95% CI is constructed for the difference of two means. The calculating the t-score in independent sample t-test is represented in Equation 5.

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}} \tag{5}$$

Where $\bar{x}_1$ and $\bar{x}_2$ are means of first and second samples, $\mu_1$ and $\mu_2$ are means of first and second samples, $s_1$ and $s_2$ are the standard deviation of first and second samples, $n_1$ and $n_2$are the size of first and second samples.

In terms of one-way ANOVA, it is assumed that each sample is taken from a normally distributed population, each sample has been drawn independently of the other samples, and the variance of data in the different groups is equal. The most common measure of effect size for a One-Way ANOVA is Eta-squared, which could be expressed as Equation 6.

$$\eta^2 = \frac{SS_B}{SS_T} \tag{6}$$

Where $SS_B$ is the sum of squares between the groups and $SS_T$ is the total sum of squares.

Using Eta-squared, 91% of the total variance is accounted for by the treatment effect. The calculating the Anova Coefficient in one-way ANOVA is represented in Equation 7.

$$F = \frac{MS_B}{MS_w} \tag{7}$$

Where $MS_B$ is the mean sum of squares between the groups and $MS_w$ is the mean sum of squares within the groups.

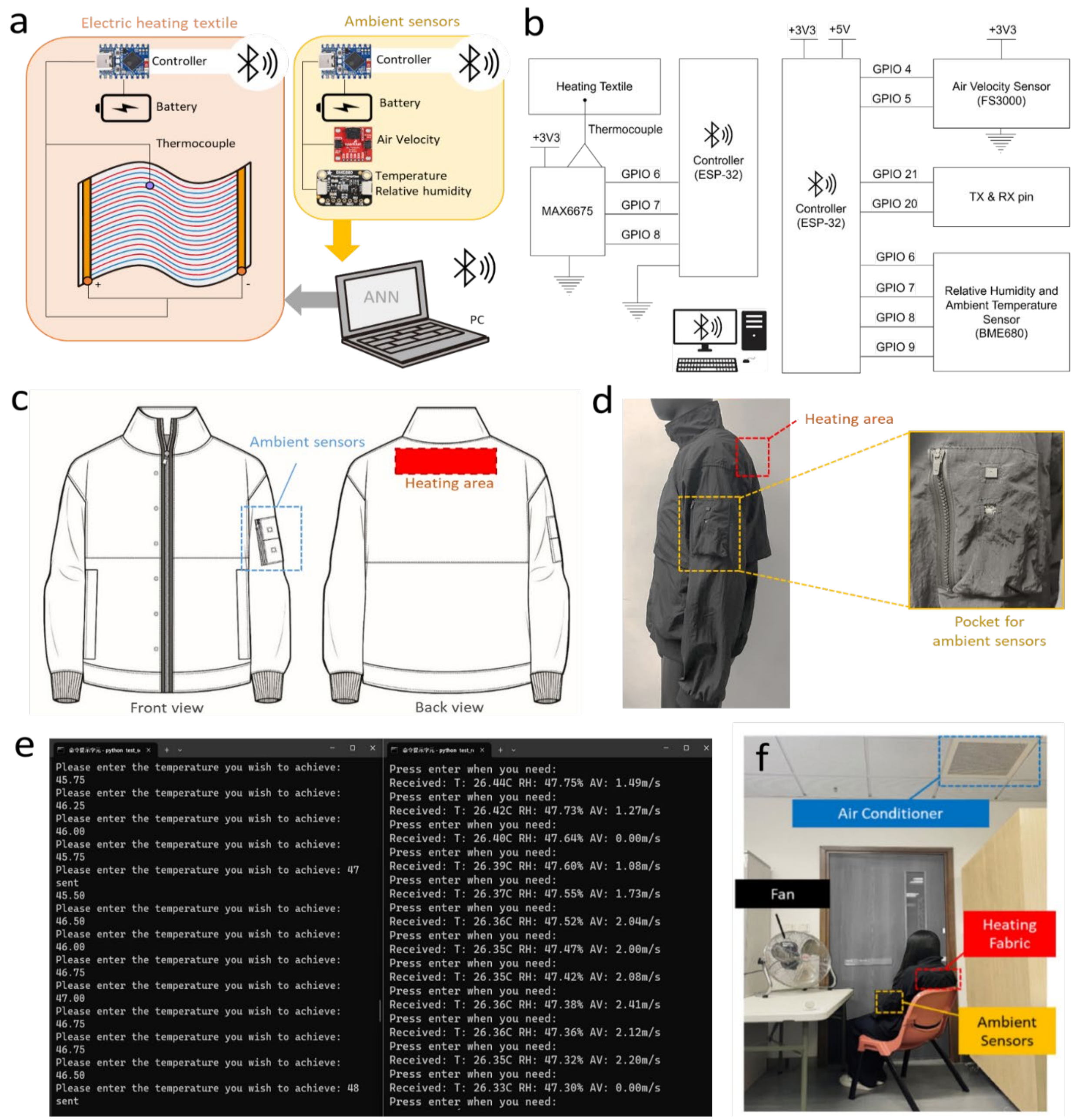


**Figure 5.** Prototype development and wearer trials: (a) Schematic illustration of Bluetooth connection for the temperature regulation system of smart heating e-textile. (b) Structure diagram of connection among ambient sensors, controller and heating e-textile. (c) Pattern design of a smart heating jacket embedded with heating e-textile and ambient sensors. (d) Image of a smart heating jacket. (e) Image captured in real-time data collection in PC. (f) Controlled environment set-up for wearer trial.

## Results and discussion

*Temperature prediction using ANN.* The actual results obtained from the ASHRAE global database of thermal comfort field measurements were compared to the temperature prediction using ANN. [56] Specifically, the comparison focused on conditions where the relative humidity ranged from 40% to 50%, as this range corresponded to the highest level of thermal comfort reported in the database. Figure 6a illustrates the correlation between the actual and ANN-predicted temperatures for different genders under these humidity conditions, utilizing both sigmoid and ReLU activation functions. Similarly, for age differences, representative age groups including 25, 35, 45, 55, and 65 were selected for comparison. Figure 6b presents the correlation between the actual and ANN-predicted temperatures for these age groups, employing both sigmoid and ReLU activation functions, under the RH range of 40% to 50%. Based on the aforementioned results, there exists a high correlation between the actual and ANN-predicted values for both the sigmoid and ReLU activation functions across all cases. Although this study is limited to conditions with relative humidity ranging from 40% to 50%, it remains a reliable preliminary test for integrating AI in heating temperature prediction, as this range corresponds to the highest level of thermal comfort reported in the database. This suggests that both activation functions can effectively predict the optimal ambient temperature to achieve maximum human thermal comfort across different age groups and genders. Previous studies have demonstrated the importance of maintaining human thermal comfort in changing thermal environments and has highlighted innovative tools for achieving this.[58-60] Developing intelligent heating textiles through AI integration for heating temperature prediction offers an innovative approach to better accommodate diverse customer needs and user preferences. This is in contrast to existing smart heating textile products, which primarily rely on Bluetooth control and PID on/off control for thermoregulation.

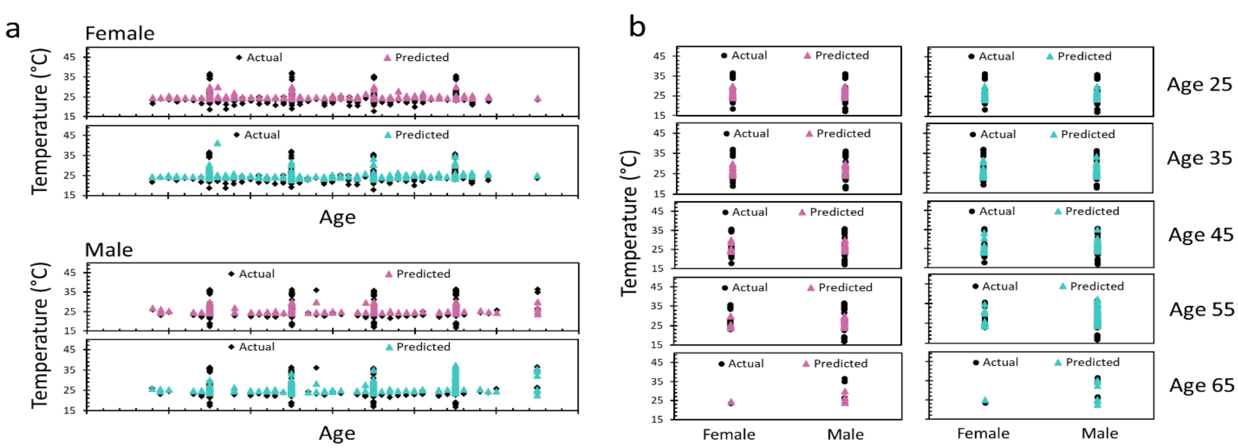

**Figure 6.** Correlation between actual and ANN predicted values using sigmoid (pink) and ReLU (green) in (a) gender and (b) age difference

*Predicted and actual heating temperature measured.* The configuration for the sigmoid activation function included 145 neurons in hidden layer 1 and 4 neurons in hidden layer 2. For the ReLU activation function, the configuration included 107 neurons in hidden layer 1 and 19 neurons in hidden layer 2. The MSE values for the sigmoid and ReLU activation functions were 6.805 and 7.539, respectively. Although both the sigmoid and ReLU activation functions exhibited a high correlation between predicted and actual values in all cases, the sigmoid activation function was chosen for the predictive model in further testing due to its minimal MSE value, i.e., 6.805. Figure 7a to 7c presented the temperature output predicted by the trained ANN model using the sigmoid activation function based on the collected 20 input data with different combinations of age, gender, relative humidity, and air velocity. The predicted outputs were summarized in graphs shown in Figures 7d and 7e, illustrating the predicted values in correlation between optimal temperature and air velocity, as well as relative humidity, respectively. Curves were plotted based on the distribution of the scattered data. The results depicted in the two graphs showed that (1) the higher the air velocity, the higher the preferred temperature, and (2) the higher the relative humidity, the lower the desired temperature according to the respondents' preferences. In relation to the results obtained from the wearer trial test, the optimal heating temperature for maximizing thermal comfort in two situations—high wind (21°C, 60%RH, 3m/s) and cold (17°C, 70%RH, 0m/s)—primarily ranged between 40°C and 50°C (Figure 7f). The relationship between participants' optimal heating temperature for maximum thermal comfort, air velocity, and relative humidity was investigated. Additionally, the optimal heating temperature of the heating jacket to achieve maximum thermal comfort for participants during the wear trial was examined. Previous studies on smart heating textiles primarily focused on integrating advanced functions, such as app control, but lacked analysis of the factors correlating with maximum thermal comfort. Understanding this correlation is crucial before developing an effective and targeted intelligent heating textile product. Further analysis of the correlation between preferred heating temperature and age and gender differences will be conducted using SPSS.

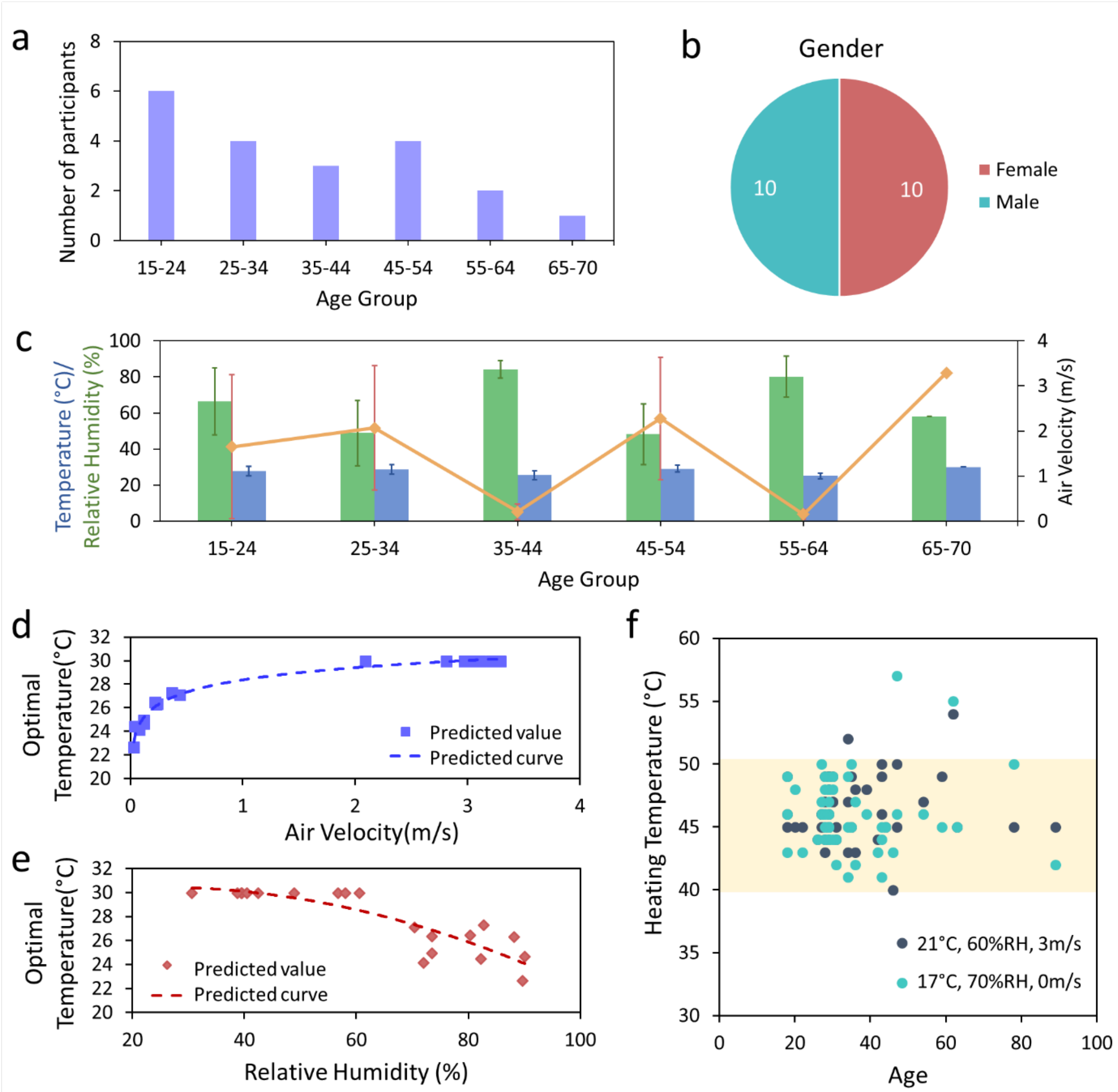


**Figure 7.** The dataset for ANN training using the sigmoid activation function included input variables such as the number of participants categorized into (a) six age groups, (b) gender differences, (c) relative humidity, and air velocity, with the output variable being optimal temperature. Predicted optimal temperature to achieve maximum thermal comfort in changes of (d) air velocity and (e) relative humidity. (f) Actual heating temperature measured in 50 wearers in wearer trial test in different ages.

*Effectiveness of the heating jacket in maintaining warmth and achieving maximum thermal comfort.* TS and CS results were compared before and after the intervention (heating e-textile).

Paired T-tests were applied for analysis. Table 1 presents the paired sample statistics, with a sample size of 50 and mean values of TS and CS before and after intervention for Case 1 (high wind, 21°C, 60%RH, 3m/s) and Case 2 (cold environment, 17°C, 70%RH, 0m/s), respectively. It also demonstrated the paired samples test for pre-post comparison. According to the student's t-distribution table, when df = 50, t=1.676. In this study, df = 49, and the t-values for pairs 1, 2, 3, and 4 were -14.347, -19.317, -10.418, and -15.913, respectively. These t-values exceed the critical values (C.V.) without considering the negative sign. The p-values for all pairs were 0.000 (<0.05), and the 95% CI in all cases does not include 0. Therefore, the findings were statistically significantly different, indicating the effectiveness of the heating jacket in maintaining warmth and achieving maximum thermal comfort. This study compared participants' thermal comfort before and after using the heating jacket prototype under the same high wind or cold environmental conditions. Optimal heating temperatures ranged between 40°C and 50°C for maximum thermal comfort were collected from all participants in the wear trial test. The results are crucial in providing evidence that this heating jacket prototype performs as effectively as standard heating jackets on the market in keeping warm, while also achieving maximum thermal comfort for participants during the wear trial. For further experimental analysis of preferred heating temperature and skin temperature differences across gender and age, the results will be accurate and reliable based on participants' optimal thermal comfort.

**Table 1.** Paired samples test for pre-post comparison

| PAIRED SAMPLES TEST | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Paired Differences | | | | | t | df | Sig. (2-tailed) |
| | | | | | 95% CI of the Difference | | | | |
| | | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | | | |
| Pair 1 | What is TS of respondents at the beginning of case 1? - What is TS of respondents at the end of the test in case 1? | -2.590 | 1.277 | .181 | -2.953 | -2.227 | -14.347 | 49 | .000 |
| Pair 2 | What is CS of respondents at the beginning of case 1? - What is CS of respondents at the end of the test in case 1? | -3.330 | 1.219 | .172 | -3.676 | -2.984 | -19.317 | 49 | .000 |
| Pair 3 | What is TS of respondents at the beginning of case 2? - What is TS of respondents at the end of the test in case 2? | -1.750 | 1.188 | .168 | -2.088 | -1.412 | -10.418 | 49 | .000 |
| Pair 4 | What is CS of respondents at the beginning of case 2? - What is CS of respondents at the end of the test in case 2? | -2.540 | 1.129 | .160 | -2.861 | -2.219 | -15.913 | 49 | .000 |

*Preferred heating temperature and skin temperature in gender differences.* To evaluate (1) whether females statistically possess a higher mean skin temperature than males when applying the heating jacket and (2) whether females statistically prefer a higher temperature than males to achieve maximum thermal comfort when applying the heating jacket, independent sample T-tests were conducted for analysis. Table 2 displays the group statistics for Case 1 and Case 2. The mean heating temperature preferred by both males and females in Case 1 was 46°C. In case 2, females (46.17°C) was slightly higher than males (45.64°C). The mean skin temperatures for males and females in Case 1 were 36.68°C and 35.61°C, respectively, while Case 2 demonstrated nearly the same temperature at 36°C. Table 3 presents the independent samples test for heating temperature preference among different genders. The hypotheses were set up as follows: $H_0$: males and females give equal mean temperatures; $H_1$: males and females do not give equal mean temperatures. There is no difference in the variance of the temperature of the heating jacket to achieve maximum thermal comfort in Case 1 and Case 2, as indicated by $F = 1.580$, $p = 0.215$ ($>\alpha=0.05$) (Case 1) and $F = 0.770$, $p = 0.385$ ($>\alpha=0.05$) (Case 2), i.e., equal variances. Additionally, there is no difference in the variance of skin temperature after testing in Case 2, as indicated by $F = 0.091$, $p = 0.764$ ($>\alpha=0.05$). However, there is a difference in the variance of skin temperature after the test in Case 1, as indicated by $F = 21.769$, $p = 0.000$ ($<\alpha=0.05$). The sample mean skin temperature for males is 1.05821 higher than that for females, and this difference (i.e., 1.05821) is statistically significant at $\alpha=0.05$ because the test statistic of $t(30) = 0.933$, $p= 0.000$ ($<\alpha=0.05$), leading to the rejection of $H_0$. Therefore, males statistically possess a higher skin temperature than females in Case 1 (high wind, 21°C, 60%RH, 3m/s). The results showed no difference in preferred heating temperatures between genders via SPSS analysis, indicating that optimal heating temperatures cannot be categorized by gender to achieve maximum thermal comfort for each user of the heating jacket. This finding suggests potential in using AI to predict optimal heating temperatures for different users in the same gender. However, despite the lack of gender differences in preferred heating temperatures, males statistically possess higher skin temperatures than females in high wind conditions. This provides safety guidance for future studies, indicating that males may have greater tolerance for higher temperatures than females. Therefore, intelligent heating textiles need to achieve maximum thermal comfort for male users while maintaining a safe heating temperature to avoid overheating.

**Table 2**. Group statistics for heating and skin temperature preferred in gender different

| GROUP STATISTICS | | | | | |
|---|---|---|---|---|---|
| | What is your gender? | N | Mean | Std. Deviation | Std. Error Mean |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 1? | Male | 14 | 46.43 | 1.910 | .510 |
| | Female | 36 | 46.44 | 2.782 | .464 |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 2? | Male | 14 | 45.64 | 2.560 | .684 |
| | Female | 36 | 46.17 | 3.368 | .561 |
| What is the skin temperature after the test in case 1? | Male | 9 | 36.6778 | 4.75349 | 1.58450 |
| | Female | 23 | 35.6196 | 1.77237 | .36957 |
| What is the skin temperature after the test in case 2? | Male | 10 | 36.4200 | 2.97538 | .94090 |
| | Female | 28 | 36.8011 | 2.74606 | .51896 |

**Table 3.** Independent samples test for heating and skin temperature preferred in gender different

| INDEPENDENT SAMPLES TEST | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% CI of the Difference Lower | Upper |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 1? | Equal variances assumed | 1.580 | .215 | -.020 | 48 | .984 | -.016 | .811 | -1.647 | 1.615 |
| | Equal variances not assumed | | | -.023 | 34.561 | .982 | -.016 | .690 | -1.417 | 1.385 |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 2? | Equal variances assumed | .770 | .385 | -.525 | 48 | .602 | -.524 | .998 | -2.531 | 1.483 |
| | Equal variances not assumed | | | -.592 | 31.145 | .558 | -.524 | .885 | -2.329 | 1.281 |
| What is the skin temperature after the test in | Equal variances assumed | 21.769 | .000 | .933 | 30 | .358 | 1.05821 | 1.13472 | -1.25920 | 3.37563 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| case 1? | Equal variances not assumed | | | .650 | 8.885 | .532 | 1.05821 | 1.62703 | -2.62968 | 4.74611 |
| What is the skin temperature after the test in case 2? | Equal variances assumed | .091 | .764 | -.369 | 36 | .714 | -.38107 | 1.03340 | -2.47690 | 1.71476 |
| | Equal variances not assumed | | | -.355 | 14.851 | .728 | -.38107 | 1.07453 | -2.67338 | 1.91123 |

*Preferred heating temperature and skin temperature in age differences.* To evaluate whether the survey data indicates that different age groups of people have significantly different heating temperatures to achieve maximum thermal comfort when applying the heating jacket, a one-way ANOVA was conducted for analysis. All respondents in the survey were grouped into six categories based on their ages: 15-24, 25-34, 35-44, 45-54, 55-64, and >65. The descriptive statistics are shown in Table S2 (Supporting Information). The hypotheses were set up as follows: $H_0$: Variance of heating and skin temperature preferred in different age groups in case 1 and case 2 are equal to each other; $H_1$: Variance of heating and skin temperature preferred in different age groups in case 1 and case 2 are not equal to each other. In Table 4 the p-values for heating and skin temperature preferred in different age groups in case 1 and case 2 are shown as $p=0.101$ (>0.05), 0.011 (<0.05), 0.404 (>0.05), and 0.284 (>0.05) respectively. There is no difference in the variance of heating temperature in case 1 and skin temperature in case 1 and case 2, but there is a difference in the temperature of the heating jacket to achieve maximum thermal comfort in case 2.

From the ANOVA table in Table 5, $H_0$: mean of heating and skin temperature preferred in different age groups in case 1 and case 2 are equal to each other; $H_1$: mean of heating and skin temperature preferred in different age groups in case 1 and case 2 are not equal to each other. $F(5,44) = 1.074$ and 0.941, $p=0.388$ (>0.05) and 0.464 (>0.05) for the mean of heating temperature in case 1 and 2 respectively. $F(4,27) = 0.207$, $p=0.932$ (>0.05) and $F(5,32) =1.757$, $p=0.150$ (>0.05) for the mean of skin temperature in case 1 and 2. The difference in mean is not statistically significant. Tukey's Honestly Significant Difference (HSD) test was applied for post-hoc comparison, as shown in Table S3 (Supporting Information). Since all p-values were greater than 0.05, the difference in temperature in all group pairs is not statistically significant. Post hoc tests were not performed for “What’s is the skin temperature after the test in case 1?” because at least one group has fewer than two cases due to missing data. To conclude, the results obtained from ANOVA analysis did not reveal significant differences in preferred heating temperature and skin temperature across age groups. This could be attributed to limitations in the validity of the dataset and the sample size within each age group for analysis. To enhance the robustness of future studies, besides increasing the sample size, it is recommended to augment the number of temperature sensors to prevent missing data due to detachment during testing.

**Table 4.** Test of homogeneity of variances for heating and skin temperature preferred in age different

| TEST OF HOMOGENEITY OF VARIANCES | | | | | |
|---|---|---|---|---|---|
| | | Levene Statistic | df1 | df2 | Sig. |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 1? | Based on Mean | 1.975 | 5 | 44 | .101 |
| | Based on Median | 1.713 | 5 | 44 | .151 |
| | Based on Median and with adjusted df | 1.713 | 5 | 27.353 | .165 |
| | Based on trimmed mean | 1.941 | 5 | 44 | .107 |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 2? | Based on Mean | 3.428 | 5 | 44 | .011 |
| | Based on Median | .816 | 5 | 44 | .545 |
| | Based on Median and with adjusted df | .816 | 5 | 11.058 | .562 |
| | Based on trimmed mean | 3.067 | 5 | 44 | .018 |
| What is the skin temperature after the test in case 1? | Based on Mean | 1.009 | 3 | 27 | .404 |
| | Based on Median | .885 | 3 | 27 | .461 |
| | Based on Median and with adjusted df | .885 | 3 | 22.549 | .464 |
| | Based on trimmed mean | .981 | 3 | 27 | .416 |
| What is the skin temperature after the test in case 2? | Based on Mean | 1.312 | 5 | 32 | .284 |
| | Based on Median | 1.078 | 5 | 32 | .391 |
| | Based on Median and with adjusted df | 1.078 | 5 | 28.540 | .393 |
| | Based on trimmed mean | 1.275 | 5 | 32 | .299 |

**Table 5**. ANOVA for heating and skin temperature preferred in age different

| ANOVA | | | | | | |
|---|---|---|---|---|---|---|
| | | Sum of Squares | df | Mean Square | F | Sig. |
| What is the temperature of heating jacket to achieve maximum thermal comfort in case 1? | Between Groups | 34.637 | 5 | 6.927 | 1.074 | .388 |
| | Within Groups | 283.683 | 44 | 6.447 | | |
| | Total | 318.320 | 49 | | | |
| What is the temperature of heating jacket to | Between Groups | 46.856 | 5 | 9.371 | .941 | .464 |
| | Within Groups | 438.124 | 44 | 9.957 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| achieve maximum thermal comfort in case 2? | Total | 484.980 | 49 | | | |
| What is the skin temperature after the test in case 1? | Between Groups | 7.640 | 4 | 1.910 | .207 | .932 |
| | Within Groups | 249.478 | 27 | 9.240 | | |
| | Total | 257.118 | 31 | | | |
| What is the skin temperature after the test in case 2? | Between Groups | 61.239 | 5 | 12.248 | 1.757 | .150 |
| | Within Groups | 223.110 | 32 | 6.972 | | |
| | Total | 284.349 | 37 | | | |

*Improvement of textile materials, fitting and application.* Feedback on the design of the smart heating jacket was gathered from 50 respondents during wearer trials for further improvement of the textile design. Among the respondents, 74% suggested adding an extra heating part at the position of the forearm/arm, while over 34% recommended warming the chest and abdomen, as illustrated in Figure 8a. Target groups for the smart heating jacket were proposed, including sportspersons (8%), elderly individuals (24%), pets (6%), and children (10%), as shown in Figure 8b. Regarding the fabric functional materials of the smart heating jacket for outdoor application, respondents suggested several properties, with 4% mentioning windproofing, 8% waterproofing, 4% washability, 4% breathability, and 2% sweat absorbency, as depicted in Figure 8c. Suggestions for design improvements were also provided, including adaptability to one's own clothes (2%), various material choices (10%), adding a cap (4%), availability in different thicknesses (4%), and availability in various styles (12%), as demonstrated in Figure 8d. Figure 8e displayed suggestions regarding fabric materials, with 10% of respondents recommending the use of windbreaker fabric, 6% suggesting a change to cotton fabric, 4% proposing a switch to fleece fabric, 2% advocating for denim fabric, and 8% expressing a desire for the availability of various materials for selection. While 24% of respondents commented on the loose fitting and sizing (Figure 8f), 4% suggested adding a cooling effect to the functionality (Figure 8g), and 2% noted the heaviness, while 4% mentioned the excessive heat generated by the electronic components (Figure 8h). The feedback from participants in wear trials is crucial for further refining the jacket design, particularly in terms of heating areas, target users, fabric material selection, and customization options. Comments highlighted priorities such as washability for daily care, adding features for outdoor use like a cap and waterproofing, and enhancing customization options such as adaptability to various clothing styles and materials. One innovative suggestion was to develop detachable heating patches that could be affixed to different garments according to user preference, allowing for greater customization. However, changes in garment form, materials, thickness, or additional finishes can affect heat loss and conductivity, requiring adjustments in power to maintain consistent heating efficiency across different garment types. These insights are crucial for developing customized intelligent heating garments, particularly for potential applications in elderly care, though safety testing remains a priority for further studies. Additionally, three-quarters of participants suggested adding an extra heating element at the forearm/arm position, indicating that a long-sleeve heating jacket may be more practical than a heating vest in future research. A limitation of this study is the testing of 50 subjects with diverse body sizes using only one standard size of heating jacket. This approach aimed to standardize testing conditions and eliminate technical errors related to sizing variations across genders and age groups. However, while all 50 subjects could fit into the heating jacket, those with smaller body sizes may have experienced cold air passing through due to the loose fit. Future improvements in sampling should restrict weight and height to ensure subjects across different genders and age groups have similar body sizes conducive to proper fitting of the heating jacket.

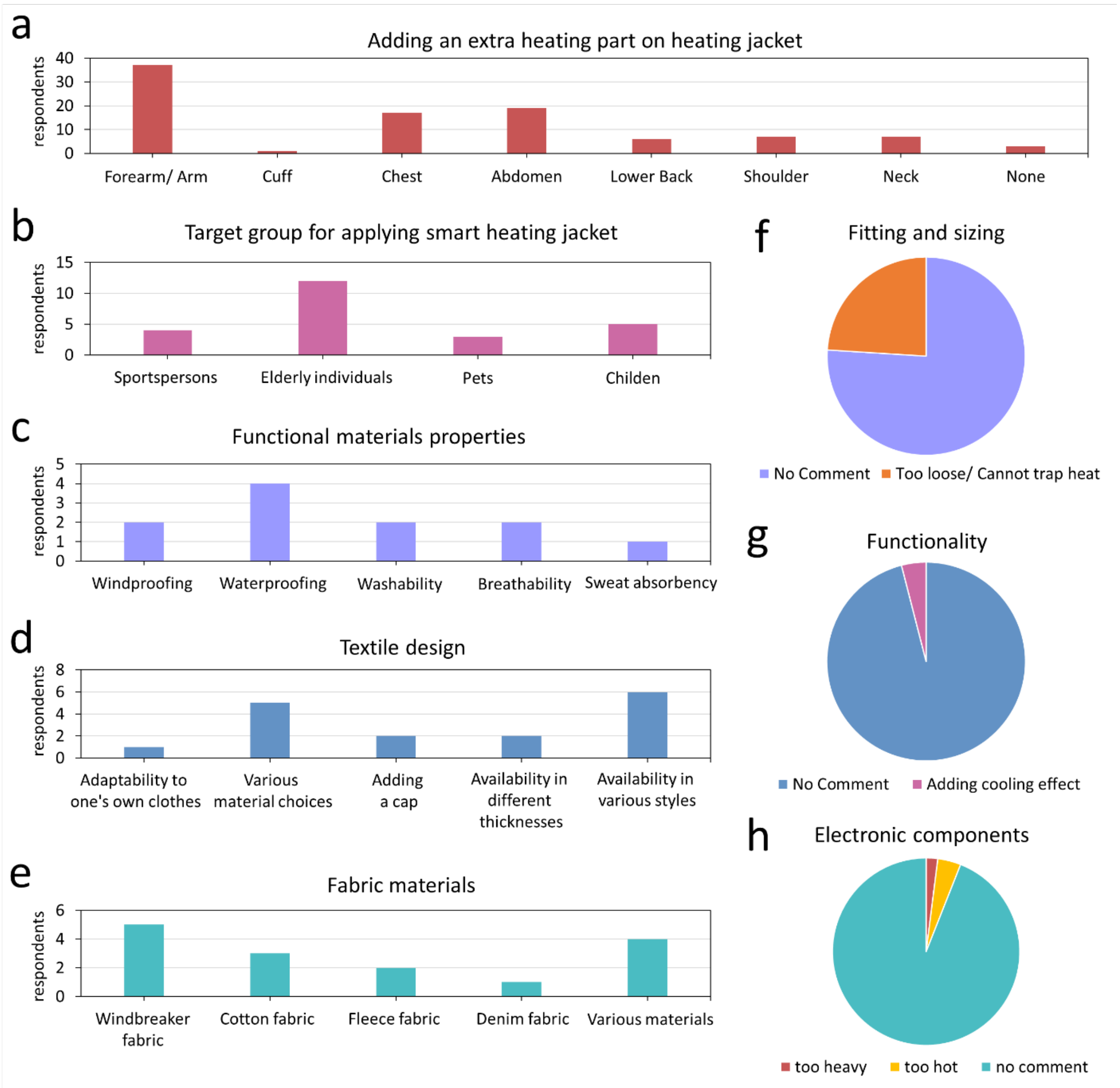


Figure 8. Improvement on textile design from questionnaires in wearer trial: (a) Suggestion in adding extra heating part on jacket. (b) Target groups suggested for applying smart heating jacket.

(c) Improvement of fabric functional materials properties. (d) Improvement on jacket design. (e) Improvement on fabric materials. (f) Comments on fitting and sizing. (g) Improvement on function. (h) Improvement on electronic components.

**Conclusion**

This study aims to evaluate the optimal thermal comfort and user preferences in the application of heating e-textiles with the aid of AI. It proposes an ANN model to predict the optimal temperature for maximum thermal comfort. Additionally, it involves the design and development of an electric heating jacket to examine preferred heating temperatures among 50 subjects with varying ages and genders. The results obtained from the ANN models indicate a promising approach, utilizing both sigmoid and ReLU activation functions in prediction. By employing the sigmoid activation function with a minimal MSE value of 6.805, the predicted temperature illustrated in the graphs show that (1) higher air velocity corresponds to a higher preferred temperature, and (2) increased relative humidity leads to a lower desired temperature according to respondents' preferences. During wearer trials, the optimal heating temperature for maximizing thermal comfort in two scenarios—case 1 (high wind, 21°C, 60%RH, 3m/s) and case 2 (cold environment, 17°C, 70%RH, 0m/s)—primarily ranged between 40°C and 50°C. Statistical analysis using SPSS demonstrates the effectiveness of the heating jacket in maintaining warmth and achieving maximum thermal comfort, with statistical significance ($p<0.05$). The results indicate that males statistically possess higher skin temperatures than females in case 1 ($p<0.05$). However, there is no evidence suggesting gender and age differences in preferred heating temperature of the heating jacket to achieve maximum thermal comfort in case 1 and case 2. Regarding improvement suggestions, over half of the respondents recommend adding heating elements at the forearm/arm position. This study represents an initial step in using ANN to predict user preferences in thermal comfort, which can be integrated with smart heating textiles in the form of jackets, vests, mats, and blankets. Future studies will focus on further integrating the ANN prediction model into heating clothing to regulate temperature based on user preferences, considering differences in age and gender. This will help analyze the effectiveness of maintaining optimal thermal comfort for diverse users in changing ambient conditions. Additionally, feedback collected from questionnaires during wear trials will be beneficial for improving textile material selection and the design of smart heating clothing. The findings in this study are anticipated to contribute to intelligent temperature regulation in thermal textiles and wearables, benefiting both the industry and consumers through customized heating products. Future studies will focus on advancing AI-based heating e-textiles.

**Declaration of conflicting interests**

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

**Funding**

This research is funded by the Laboratory for Artificial Intelligence in Design (Project Code: RP3-5) under InnoHK Research Clusters, Hong Kong Special Administrative Region.

## References

1. Nakamura M, Yoda T, Crawshaw LI, et al. Relative importance of different surface regions for thermal comfort in humans. *Eur. J. Appl. Physiol.* 2013; 113: 63–76.

2. Enescu D. A review of thermal comfort models and indicators for indoor environments. *Renew. Sustain. Energy Rev.* 2017; 79: 1353–1379.

3. Liu C, Tang Y, Sun L, et al. Effects of local heating of body on human thermal sensation and thermal comfort. *J. Build. Eng.* 2022; 53: 104543.

4. Hsu P-C, Liu X, Liu C, et al. Personal thermal management by metallic nanowire-coated textile. *Nano Lett.* 2015; 15: 365–371.

5. He Y, Wang X, Li N, et al. Heating chair assisted by leg-warmer: A potential way to achieve better thermal comfort and greater energy conservation in winter. *Energy Build.* 2018; 158: 1106–1116.

6. Fang Y, Chen G, Bick M, et al. Smart textiles for personalized thermoregulation. *Chem. Soc. Rev.* 2021; 50: 9357–9374.

7. Fiala D. *Dynamic simulation of human heat transfer and thermal comfort*. PhD Thesis, De Montfort University Leicester, UK, 1998, p.1.

8. Lee C, Tan J, Lam NYK, et al. The effectiveness of e-textiles in providing thermal comfort: A systematic review and meta-analysis. *Text. Res. J.* 2023; 93: 1568–1586.

9. Song W, Lu Y, Liu Y, et al. Effect of partial-body heating on thermal comfort and sleep quality of young female adults in a cold indoor environment. *Build. Environ.* 2020; 169: 106585.

10. Song WF, Zhang CJ, Lai DD, et al. Use of a novel smart heating sleeping bag to improve wearers' local thermal comfort in the feet. *Sci. Rep.* 2016; 6: 19326.

11. Kim S, Hong K and Lee H. Tolerable range of abdomen and waist skin temperature for heating-capable smart garments. *IJCST* 2021; 33: 929–941.

12. Sormunen E, Rissanen S, Oksa J, et al. Muscular activity and thermal responses in men and women during repetitive work in cold environments. *Ergon.* 2009; 52: 964–976.

13. Chen Z, Li J, Song W, et al. Smart wireless charging heating insoles: Improving body thermal comfort of young males in an extremely cold environment. *CTRJ* 2022; 40: 220–234.

14. Zhang C, Ren C, Li Y, et al. Designing a smart electrically heated sleeping bag to improve wearers' feet thermal comfort while sleeping in a cold ambient environment. *Text. Res. J.* 2017; 87: 1251–1260.

15. Roh J-S and Kim S. All-fabric intelligent temperature regulation system for smart clothing applications. *J. Intell. Mater. Syst. Struct.* 2016; 27: 1165–1175.

16. Hamdani STA, Potluri P and Fernando A. Thermo-mechanical behavior of textile heating fabric based on silver coated polymeric yarn. *Mater.* 2013; 6: 1072–1089.

17. Bahadir SK and Sahin UK. A wearable heating system with a controllable e-textile-based thermal panel. *Wearable Technol.* 2018; 175.

18. Repon MR and Mikučionienė D. Progress in flexible electronic textile for heating application: A critical review. *Mater.* 2021; 14: 6540.

19. Smart textiles - product development around textile current circuits. warmX., https://www.warmx.de/index.php/industry-and-research.html (accessed 1 April 2024).

20. Hong Kong: Heat-conductive textile: Stylish. KnitWarm. https://zh.knitwarm.com/ (accessed 2 April 2024).

21. Mun J-H, Jeon J-H, Jung Y-J, et al. The factors associated with contact burns from therapeutic modalities. *Ann. Rehabil. Med.* 2012; 36: 688.

22. Sahta I, Baltina I, Blums J, et al. The control of human thermal comfort by the smart

clothing. In: *SHS Web Conf.* 2014, p.00040. EDP Sciences.
23. Fang S, Wang R, Ni H, et al. A review of flexible electric heating element and electric heating garments. *J. Ind. Text.* 2022; 51: 101S–136S.
24. KWON D-H, KO J-H, HUR G-Y, et al. Contacts burns caused by electric pad. *J Korean Burn Soc.* 2012: 9–14.
25. Guergova S and Dufour A. Thermal sensitivity in the elderly: a review. *Ageing Res. Rev.* 2011; 10: 80–92.
26. DeLisa JA, Gans BM and Walsh NE. *Physical medicine and rehabilitation: principles and practice*. Lippincott Williams & Wilkins, 2005. p.587.
27. Kobersi IS, Finaev VI, Almasani SA, et al. Control of the heating system with fuzzy logic. *World Appl. Sci. J.* 2013; 23: 1441–1447.
28. Rabik MM and Muthuramalingam T. Tracking and locking system for shooter with sensory noise cancellation. *IEEE Sens. J.* 2017; 18: 732–735.
29. Kiekens P and Jayaraman S. *Intelligent textiles and clothing for ballistic and NBC protection: technology at the cutting edge*. Springer Science & Business Media, 2012. p. 20.
30. Rantanen J, Vuorela T, Kukkonen K, et al. Improving human thermal comfort with smart clothing. In: *2001 IEEE Int. Conf. Syst. Man. Cybern.* (Cat No 01CH37236) 2001, pp.795–800. IEEE.
31. Wu J-X and Liao Y-C. Self-regulated thermal comfort control for wearable heating device. *J. Taiwan Inst. Chem. Eng.* 2021; 121: 74–80.
32. Wu Y, Wang Z, Xiao P, et al. Development of smart heating clothing for the elderly. *J. Text. Inst.* 2022; 113: 2358–2368.
33. Hong S, Gu Y, Seo JK, et al. Wearable thermoelectrics for personalized thermoregulation. *Sci. Adv.* 2019; 5: eaaw0536.
34. Khan PF, Sengottuvel S, Patel R, et al. Design and implementation of a discrete-time proportional integral (PI) controller for the temperature control of a heating pad. *SLAS Technol.* 2018; 23: 614–623.
35. Johnson MA and Moradi MH. *PID control*. Springer, 2005. p.110.
36. Veit D. Fuzzy logic and its application to textile technology. *Simulation in Textile Technology*. Elsevier, 2012, pp.112–141.
37. Gouda M, Danaher S and Underwood C. Thermal comfort based fuzzy logic controller. *Build. Serv. Eng. Res. Technol.* 2001; 22: 237–253.
38. Mendel J, Hagras H, Tan W-W, et al. *Introduction to type-2 fuzzy logic control: theory and applications*. John Wiley & Sons, 2014. p.4.
39. Anand A, S. Applications of fuzzy logic in renewable energy systems–a review. *Renew. Sustain. Energy Rev.* , 2015, pp.585–607.
40. Kirstein T. *Multidisciplinary know-how for smart-textiles developers*. Elsevier, 2013. p.20.
41. Šahta I, Baltina I, Truskovska N, et al. Selection of conductive yarns for knitting an electrical heating element. *WIT Trans Built Environ* 2014; 137: 91–102.
42. Luo X, Hou W, Li Y, et al. A fuzzy neural network model for predicting clothing thermal comfort. *Comput. Math. Appl.* 2007; 53: 1840–1846.
43. Vu CC and Kim J. Human motion recognition using SWCNT textile sensor and fuzzy inference system based smart wearable. *Sens. Actuat. A-phys.* 2018; 283: 263–272.
44. Muthuramalingam T, Rabik MM, Saravanakumar D, et al. Sensor integration-based approach for automatic fork lift trucks. *IEEE Sens. J.* 2017; 18: 736–740.
45. Wang S-C and Wang S-C. Artificial neural network. *Interdisciplinary computing in java*

*programming* 2003: 81–100.
45. Jang J-S. ANFIS: adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Man. Cybern.* 1993; 23: 665–685.
46. Siler W and Buckley JJ. *Fuzzy expert systems and fuzzy reasoning*. John Wiley & Sons, 2005, p.220.
47. Haykin S. *Neural networks: a comprehensive foundation*. Prentice Hall PTR, 1998.
48. Wang S-C and Wang S-C. Artificial neural network. *Interdisciplinary computing in java programming* 2003: pp.81–100.
49. Hertz JA. *Introduction to the theory of neural computation*. Crc Press, 2018, pp.111–159
50. Bishop CM. *Neural networks for pattern recognition*. Oxford university press, 1995, p.148.
51. Bishop CM. Pattern recognition and machine learning. *Springer google Sch.* 2006; 2: 645–678.
52. LeCun Y, Bengio Y and Hinton G. Deep learning. *Nat.* 2015; 521: 436–444.
53. Goodfellow I, Bengio Y and Courville A. *Deep learning*. MIT press, 2016, p.455.
54. Dawson CW and Wilby R. An artificial neural network approach to rainfall-runoff modelling. *Hydrol. Sci. J.* 1998; 43: 47–66.
55. Pereira F, Carvalho V, Vasconcelos R, et al. A review in the use of artificial intelligence in textile industry. In: *Inno. Mech. Eng.* 2022, pp.377–392. Springer.
56. DRYAD. ASHRAE global database of thermal comfort field measurements, https://datadryad.org/stash/dataset/doi:10.6078/D1F671 (2022, accessed 29 August 2023).
57. Scikit-learn Machine Learning in Python, https://scikit-learn.org/stable/ (accessed 29 August 2023).
58. Han, X., Hu, Z., Li, C., Wu, J., Li, C., & Sun, B. (2023). Prediction of human thermal comfort preference based on supervised learning. *J. Therm. Biol.* 112, 103484.
59. Su, X., Yuan, Y., Wang, Z., Liu, W., Lan, L., & Lian, Z. (2023). Human thermal comfort in non-uniform thermal environments: A review. *Energy Built Environ.* 5(6), 853–862.
60. Chen, F., Fu, M., Li, Y., Shen, S., Yang, J., & Weng, W. (2023). A numerical tool for assessing human thermal safety and thermal comfort in cold-weather activities. *Int. J. Biometeorol.* 67(2), 377–388.