Doctoral Dissertation (Shinshu University)

Study on evaluation method for clothing comfort sensation using psychophysiological measurement and its non-linear analysis

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Table Content

Chapter1. Introduction

1.1 Background

1.1.1 Factors of clothing comfort sensation

Wearing clothes is a part of daily life. The main functions of wearing clothing are controlling the temperature and humidity near the surface of the body, protecting the body and skin, hiding or emphasizing parts of the body, decorating the body, and indicating gender, status, and occupation [1]. Although the origins of clothing are not clear, there is evidence that it has been used by humans for a very long time. Animal fur coats found with mummies in the Ötzal Italian Alps have been dated to approximately 5,300 years ago. Mitochondrial analysis suggests that Chalcolithic people used specific clothing materials, and wore clothing to protect themselves against the cold [2]. Thus, clothing has been a part of human life since ancient times, and the use of clothing in human societies is ubiquitous. Consequently, enhancing the sensation of comfort associated with clothing is important for enabling people to live comfortable lives.

Three basic categories have been widely used to define clothing comfort sensation, which encompass the psychological, physical, and physiological factors involved in interactions between humans and the environment (shown in Figure 1.1) [3-10]. Each aspect is important in relation to context and preferences. In addition, each aspect of comfort is influenced by different attributes within the cloth-wearer-environment. It is important to classify and explain these types of comfort-related perceptions and their stimuli.

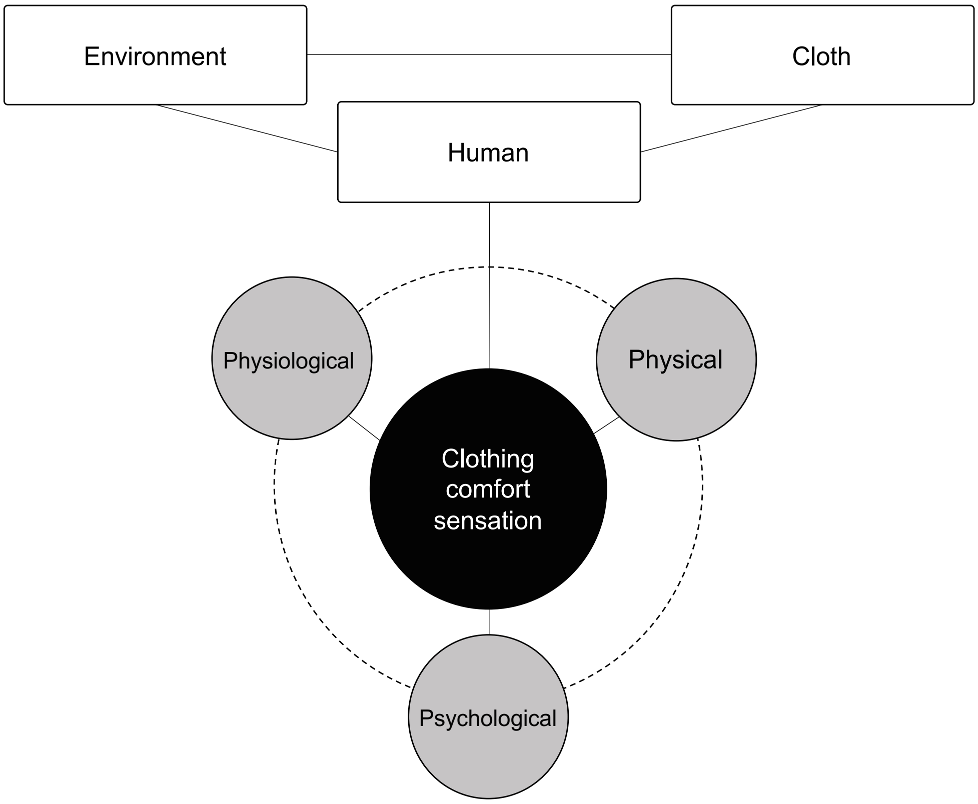


Figure 1.1. The three basic categories of clothing comfort sensation in humans

Physical comfort includes a range of sensations when a garment touches the wearer's skin, in whole or in part [10]. The sensation of comfort is caused by the stimulation of various sensory receptors (including heat receptors and mechanoreceptors) by the physical stimulation induced by the interaction between skin and clothing. According to Harada, three main factors determine the clothing comfort of garments: the climate within the clothing, the texture of the clothing, and pressure acting on the clothing [62]. The Kawabata Evaluation System was developed to quantitatively measure properties related to physical comfort. The texture of fabrics (Hand Values) can be evaluated quantitatively using this system [11-13].

Psychological comfort focuses on the comfort of individuals in relation to their roles, values, and social identity [9]. Comfort is subjectively formulated on the basis of a person's previous experience and their internal feelings, as well as the overall perception of sensory sensations from neurophysiological sensory signals via the evaluation of several perceived sensations [14]. Physical stimulation, the social and cultural environment, emotional, cognitive, and mental states are all factors that influence the psychological characteristics of the sensation of comfort.

Physiological comfort primarily comprises thermal comfort and bodily mechanisms. Thermal comfort is associated with thermoregulation and the regulation between the production and loss of body temperature [9]. British Standards, as expressed in BSEN ISO 7730, define thermal comfort as "a state of mind that represents satisfaction with the thermal environment." In addition to environmental factors, the physiological comfort of the body is affected by changes in the respiratory system, central nervous system, autonomic nervous system, skeletal muscular system, and digestive system [14-16].

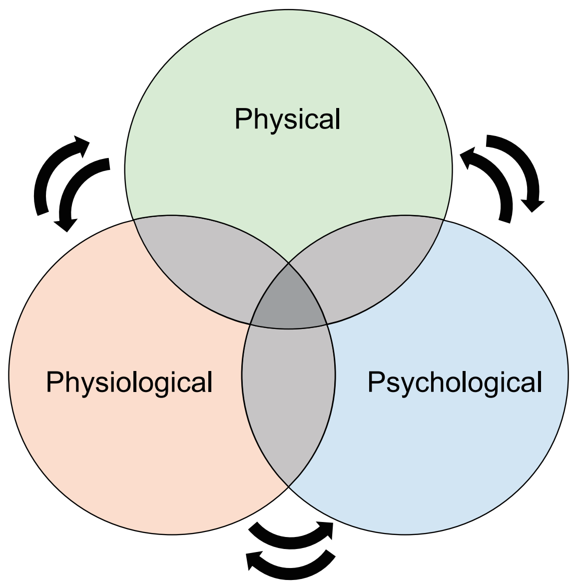


Figure 1.2. Relationships of the three elements of the clothing comfort sensation

Although the three comfort elements have independent components, each element influences the others, as shown in Figure 1.2. For example, physical comfort caused by physical stimuli evokes psychological and physiological responses between the wearer and clothing, while psychological fluctuations also evoke physiological responses. Additionally, the fluctuations of psychological responses themselves also influence physiological responses. These processes are cyclical, and when one stimulus induces one aspect, that aspect also affects the other. Finally, the combination of these factors constitutes the complete clothing comfort sensation [46]. In this way, the clothing comfort sensation involves complex components with independent elements, as well as elements that are related to each other. Thus, to evaluate clothing comfort sensation, it is important not only to measure the physical characteristics of the fabric, but also to evaluate the wearer's physiological and psychological characteristics. Clarifying the relationship between wearers' psychological and physiological responses is an important aspect of clothing design to help people live comfortably.

1.1.2 Conventional evaluation methods for measuring clothing comfort sensation

Many previous studies have attempted to measure psychophysiological responses to evaluate clothing comfort sensation. General linear analysis methods, such as correlation analysis and multivariate analysis, are usually performed on measured data. Because the calculations in linear analysis are relatively simple, it is possible to analyze a small amount of data with a low calculation cost. The results and relationships can be understood easily in the analysis.

The most common type of study design in this area involves evaluating clothing comfort sensation using subjective evaluation of psychological sensations [17,18]. Such studies have also been used in product evaluation, investigating the correspondence between the properties of clothing materials and subjective ratings of wearers using correlation analysis.

In addition, several studies have attempted to examine human physiological responses in addition to subjective sensations. In one well known example, measurements of thermal physiological responses such as body temperature and perspiration were used as thermal indicators [17,18]. These measures were performed by analyzing thermal physiological indicators such as changes of skin temperature in addition to subjective evaluation and assessment of material properties.

In some physiological measurement methods, the activity of the nervous system is measured to evaluate clothing comfort sensation. As shown in Figure 1.3, the nervous system comprises two main components: the central nervous system and the peripheral nervous system.

Electroencephalography (EEG) is widely used for the measurement of central nervous system activity. One study reported that EEG measurement may be effective for evaluating the sensation of warmth by clarifying differences in brain waves when putting on and taking off clothes [19]. In addition, sandpaper, which is considered to cause an uncomfortable sensation, was reported to induce lower α-wave power and a larger amplitude of the event-related P-300 (reflecting activation of brain function), compared with blankets and cotton cloth, which are soft materials [20]. In another study, EEG after sweating was measured while participants wore undershirt made of materials with different levels of hygroscopicity, to investigate the relationship with skin contact sensations such as stuffiness and stickiness [21]. The results indicated that frequency analysis of brain waves can be applied to the measurement of subjective sensations such as differences in skin irritation and discomfort caused by undershirt after sweating.

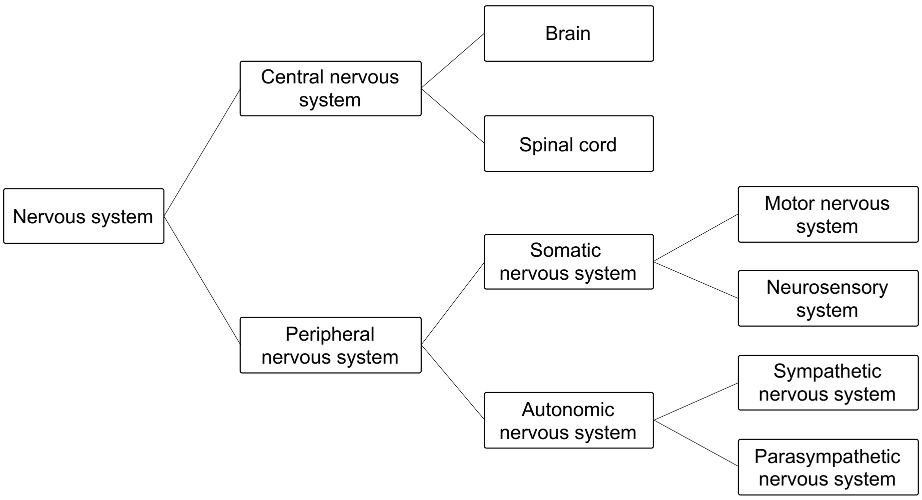


Figure 1.3. Structure of the human nervous system

Measurement of the autonomic nervous system has mainly been used to examine the activity of the peripheral nervous system. One study reported that high-frequency (HF) power calculated from heart rate variability tended to be greater when participants wore comfortable pajamas compared with when they wore uncomfortable (wrinkling) pajamas [22]. Another study reported that wearing undershirt made from materials with high moisture transfer characteristics was less likely to increase sympathetic nervous system activity [23]. Furthermore, regarding the effects of the fabric texture of clothing, one study reported that parasympathetic activity was increased when participants wore clothing that was soft to the touch [24].

The studies described above suggest the effectiveness of evaluating clothing comfort sensation by measuring subjective psychological sensations, thermophysical indices, and the activity of the nervous system using general linear analysis. Thus, it appears to be possible to evaluate the relationship between clothing comfort sensation and various factors, including physical, psychological, and physiological components.

1.1.3 Proposal of evaluation method using artificial neural networks

In most of the previous studies mentioned above, general linear analysis was performed as a conventional evaluation method. However, sensations in humans do not always exhibit linear changes in response to changes in presented stimuli. For example, Ernst Weber discovered Weber's Law. According to Weber’s Law, the threshold for discrimination between two stimuli increases in proportion to the stimulus intensity for many parameters [25]. Consequently, Gustav Fechner explained Weber’s law by assuming that external stimuli are scaled to a logarithmic internal representation of the sensation [25]. In addition, Stevens et al. reported an exponential relationship between the brightness of stimuli and the sensation of brightness [26]. These findings suggest that non-linear analytical approaches may be useful for the evaluation of clothing comfort sensation, and could potentially provide greater accuracy than conventional linear analysis.

In the current study, an artificial neural network (ANN) was used as a non-linear analysis method. ANNs are models that simulate networks of nerve cells (neurons) in the brain of an organism. ANNs typically have a three-layer structure consisting of an input layer, a hidden layer, and an output layer. When measurable values of physiological indicators and psychological sensations are input to the input layer, the values pass through the hidden layer. Finally, the values corresponding to a higher-order concept, such as the clothing comfort sensation, are output to the output layer. Back-propagation can be used as a learning method for ANNs. This learning method modifies the connection load between neurons in a direction to reduce the error between the teacher signal and the output value of the ANN. This process allows non-linear discrimination. Because ANNs have non-linear discrimination ability and self-organizing ability, it is possible to recognize patterns corresponding to deformation and ambiguity, and recognition ability can be achieved with human-like flexibility. Table 1.1. shows the advantages and disadvantages of non-linear analysis using ANNs [63]. The flexibility of non-linear analysis can be calculated using many features. As a disadvantages of this analysis, the relationships may be over-fitted, and it may not be possible to handle general data when only a small amount of data is used. In addition, the cost of calculation involved in non-linear analysis is much higher than that for conventional linear analysis. However, computational power has improved in recent years, increasing the ability to perform the calculations involved in non-linear analysis. Moreover, from the perspective of data measurement technology, some methods enable data to be collected easily. For example, fabric-based sensing is a major research field in biomedical science and textile engineering [64] and the development of technologies involving wearable sensors for collecting data using electrocardiography (ECG) and thermo-physiological indices is also progressing [38, 39]. Because of the improvement of calculation technologies and the ease of collecting measurement data, it is easier to perform nonlinear analysis that requires a large amount of data and complex calculations. When targeting human sensations and responses, non-linear analysis methods using new technologies may be more effective than conventional linear analysis. Thus, these methods may be suitable for evaluating clothing comfort sensation.

Table 1.1. Advantages and disadvantages of non-linear analysis using ANNs

Advantages	Disadvantages (compared to linear model)
High accuracy	High computational cost
Using many features	Need a lot of data
Flexible calculations of the relationships	Risk of overfitting with a small amount of data
Discovering relationships that are difficult to imagine easily	Difficulty of understanding the result

Although ANN methods have been applied to solve textile production problems [27-34], few studies have examined the application of ANNs for elucidating subjective clothing comfort sensation for the wearer because of their disadvantages. In one previous study involving comfort evaluation using an ANN, evaluation of the comfort of a skirt was performed using a small-scale ANN with data regarding the wearer's body shape, product material, and pattern [35]. Another study using an ANN investigated the predictability of the sensation of comfort from other psychological sensations using the ANN. The results revealed a strong correlation between predicted and actual comfort ratings (r = 0.817) [35]. These findings suggest that overall comfort performance could be predicted using ANNs.

Only a small number of attempts have been made to use ANNs to predict the clothing comfort sensation from the wearer's body shape [35], material data [37], and psychological sensation data [36], and no previous studies have attempted to predict the clothing comfort sensation by including the physiological responses of the wearer as a feature. Evaluating the clothing comfort sensation via ANN analysis using physiological responses as input data may be an effective approach because physiological responses are one of the three elements of the clothing comfort sensation, and previous studies using conventional analysis methods reported the effectiveness of measuring physiological responses.

1.2 Purpose and overview of the current thesis

The overall goal of the current thesis was to verify the effectiveness of a method for evaluating the clothing comfort sensation using an ANN. Figure 1.4 shows an overview of this thesis. In this thesis, an undershirt was the subject of clothing comfort evaluation. Undershirts were selected as the research target, as clothing items that strongly affect the clothing comfort sensation because they are in close contact with the human body. In this thesis, a wide range of material properties of undershirts and wearers' physiological and psychological responses were measured to evaluate clothing comfort sensation using numerical analysis.

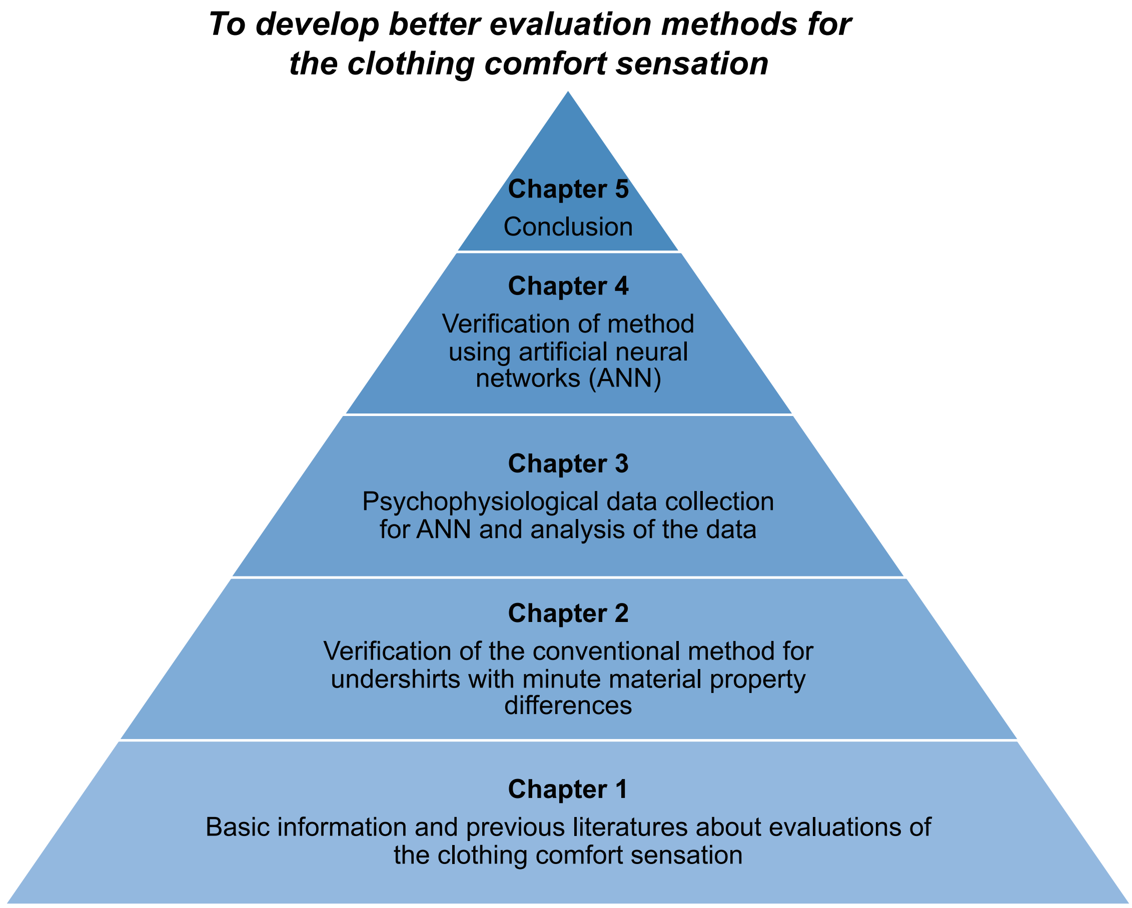


Figure 1.4. Overview of this thesis

As a first step toward the overall research goal of this thesis, in Chapter 2, a conventional linear analysis method was first investigated. Although previous studies clarified the relationships among clothing comfort sensations and other psychological sensations and physiological indices, the stimulation conditions of the fabric samples were simplistic and varied widely. The effectiveness of measuring and evaluating physiological responses for undershirts with similar properties has not been completely clarified. Undershirt samples with minute material property differences were prepared, and the effectiveness of psychophysiological response measurement was assessed to clarify the relationships between psychological sensations and physiological indices. Regarding indices for measuring physiological responses, the most commonly used techniques are thermal physiological indices such as thermal sweating and body temperature, autonomic nervous system activity indices such as ECG, and central nervous system activity indices such as EEG. Thermal physiological indices and autonomic nervous system activity indices were the main focus in this thesis because the technologies for measuring the indices are progressing as wearable sensors [38, 39]. Thus, it is likely that easy and comfortable data collection in daily life will be possible in future.

Chapter 3 reports psychophysiological data collection for ANN analysis, and describes the characteristics of the collected data. Specifically, changes in physiological and psychological responses were investigated, and the psychological structure of clothing comfort sensation was analyzed when the material of the undershirt samples was changed.

Finally, in Chapter 4, the evaluation method using ANN with data obtained from the physiological and psychological responses in Chapter 3 was verified. The relationship between the prediction accuracy of ANN with input psychophysiological response data was investigated. In addition, the effectiveness of the evaluation method using ANN was verified by comparison with the predictions of a conventional linear analysis method.

Through the series of experiments described above, the current thesis sought to clarify the effectiveness of using ANN with psychophysiological response measurement for the evaluation of clothing comfort sensation. This research aimed to develop more accurate methods for evaluating wearers' clothing comfort sensation using complex non-linear analysis (Figure 1.5). The achievements in this thesis may be helpful for informing the development of products that improve the comfort sensation for wearers in the future. Additionally, the current method may be useful as an analysis tool for elucidating clothing comfort sensation using many different types of data.

All of experiments in this thesis were conducted with the approval of Shinshu university's ethical committee for research on humans.

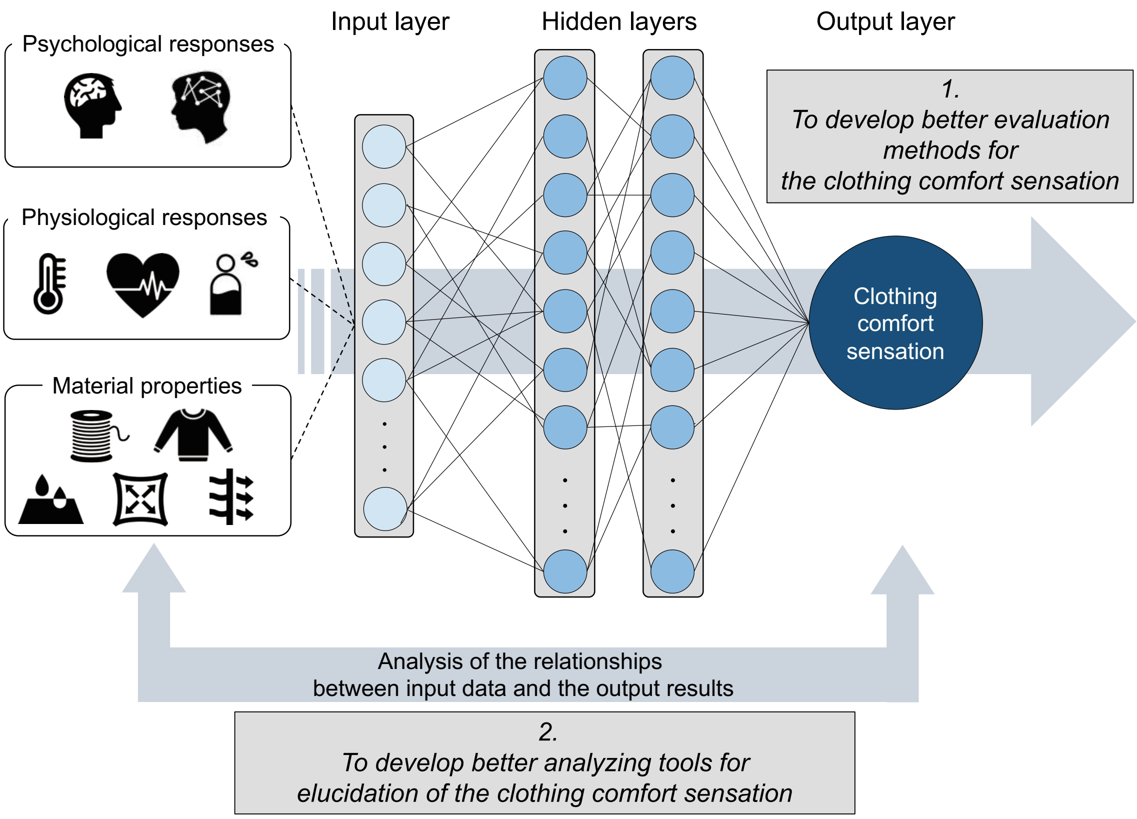


Figure 1.5. Possibility of development of evaluation methods for clothing comfort sensation using ANNs

Chapter 2. Verification of a conventional evaluation method for assessing the clothing comfort sensation of undershirts with minute material property differences

2.1 Introduction

As mentioned in Chapter 1, previous studies reported the effectiveness of methods involving the measurement of psychophysiological responses for evaluating clothing comfort sensation. However, in these previous studies, the stimulation conditions of the samples were simplistic and varied widely. The effectiveness of measuring and evaluating psychophysiological responses for undershirts with similar properties has not been clarified in detail.

In this chapter, therefore, the effectiveness of measuring physiological psychological responses was confirmed by examining undershirts with very small differences in material properties. Undershirts were prepared using the same hydrophobic fiber materials with other similar material properties, namely polyester (polyethylene terephthalate [PET]) and polypropylene (PP). Psychophysiological responses were measured during the state of sweating induced by exercise as a complex situation.

The purpose of the current chapter was to verify the effectiveness of conventional comfort evaluation by measuring psychophysiological responses when wearing clothing with minute differences in material properties, before conducting evaluation using ANN.

2.2 Methods

2.2.1 Materials

The yarn samples were two types of yarn: PP and PET yarns. These fibers are hydrophobic and have a zero or very low moisture content [40] as shown in Figure 2.1. These fiber materials have relatively similar properties in terms of thermal and moisture transport properties. Therefore, these two kinds of fibers were used as the materials in this chapter. Generally, a highly absorbent fiber material such as cotton is used for undershirts, but this experiment had the background of aiming at the design of undershirts that allow moisture to easily transport from the skin side to the outside when sweating. Therefore, the hydrophobic fibers such as PET and PP were used as the materials.

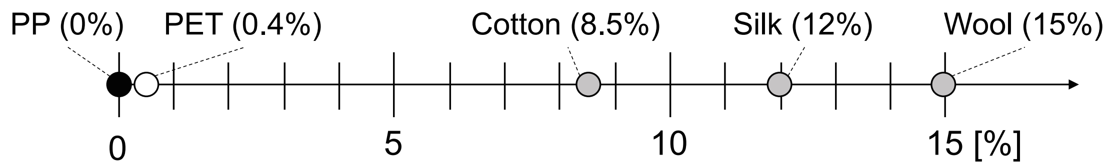


Figure 2.1. Moisture content of fibers at 20 ºC and 65% R.H

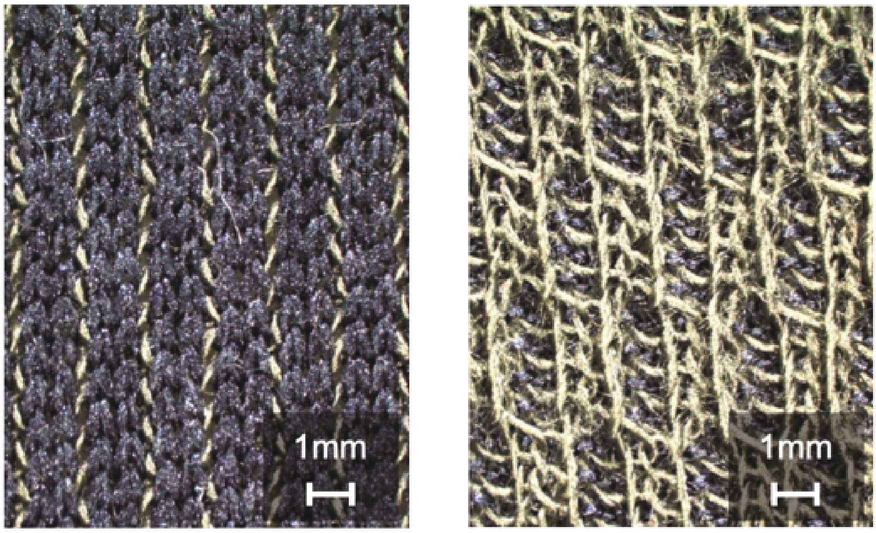
Table 2.1 shows the specifications of the two types of yarn. Knitted fabric shirts were prepared using these yarns on the skin side. Table 2.2 shows the knitting structure of the undershirt samples and the mixing ratio of the materials used in the fabrics. Two types of turtleneck T-shirt were made. The knitting structures were unified with two-layer structures of honeycomb on the skin side and a plain stich on the outside (Figure 2.2). The two-layer structures were chosen to create more minute differences in material properties simply by changing only the part of the yarn sample that touches the skin surface. Additionally, it aimed at the design of undershirts that allow moisture to easily transport from the skin side to the outside when sweating as a background. On the outside, all samples were unified with PET, and the material on the skin side differed depending on the sample. The skin side of the PET/PP structure was PP yarn while the skin side of the PET/PET structure was PET yarn.

Table 2.1. Specifications of the two types of yarn samples

	PP	PET
Material	Polypropylene spun yarn 100%	Polyester spun yarn 100%
Fineness of fiber [dtex]	1.80	1.32
Fineness of yarn [tex]	15.2	14.9
Diameter [mm]	0.221	0.209
Number of twists [/inch]	22.33	20.68
Twist factor [-]	3.53	3.27
The number of hairiness [n/10m]	0	1
Porosity [%]	56.4	52.2
Elongation [%]	21.9	13.1
U% [%]	11.21	8.4

Table 2.2. Knitting structure of the undershirt samples and mixing ratio

Fabric sample	Knitting structure and material		Total mixing ratio [%]
	Outside: Plain stich	Skin side: Honeycomb	
PET/PP	Polyester yarn 100%	Polypropylene yarn 100%	Polyester 44% / Polypropylene 56%
PET/PET		Polyester yarn 100%	Polyester 100%



(a) Outside (b) Skin side

Figure 2.2. Knitting structures of fabric samples;

(a) outside of fabrics (plain stich), (b) skin side of fabrics (honeycomb)

2.2.2 Confirmation of subtle differences in material properties between samples

In order to confirm the subtle difference in the material properties of the two types of fabric samples, various material properties of the fabric samples were measured.

All of the experiments were conducted at 20 ± 1°C in an environment with a relative humidity of 65 ± 3%. These environmental conditions were in accordance with the relevant Japanese Industrial Standard (JIS); JIS L 0105. The specimens were kept in the environment described for at least 24 h before the measurements were carried out. The properties of fabric surface on the skin side were investigated. The skin side meant the side in contact with the skin while the undershirt was being worn. Each measurement was performed five times, and the mean value and standard deviation were calculated. The values for the material properties were used to assess the psychophysiological indices from the wearing experiment.

The properties of bending, compression, surface, heat-transfer and air permeability were determined using a KES-FB System (Kato Tech, Inc., Kyoto, Japan) [11-13]. The moisture-transfer properties of the fabric samples were evaluated using the BOKEN method (BQE A 028) [41]. This method was used to measure the wicking and drying rate at 20 min.

Table 2.3 shows the mean values and standard deviations of the material properties and results of significant differences between samples obtained in a Student's t-test. The above measurements of the material properties of PET/PP and PET/PET samples revealed the following features.

Table 2.3. Mean values and standard deviations of the material properties and results of significant differences between samples

Blocked Property	Property		PET/PP Mean	±	SD	PET/PET Mean	±	SD	Significant difference **p<0.01, *p<0.05
Bending	B: Bending rigidity [gf・cm^2/cm]	wale	0.011	±	0.001	0.014	±	0.001	**
		course	0.011	±	0.001	0.007	±	0.001	**
	2HB: Hysteresis of bending moment [gf・cm/cm]	wale	0.006	±	0.000	0.008	±	0.001	**
		course	0.007	±	0.000	0.002	±	0.000	**
Compression	LC: Linearity of compression-thickness curve [-]		0.42	±	0.01	0.52	±	0.01	**
	WC: Compression Energy [gf・cm/cm^2]		0.36	±	0.01	0.76	±	0.01	**
	RC: Compressional resilience [%]		47.5	±	0.9	51.2	±	1.0	**
	TO: Thickness under 0.5 gf/cm^2 load [mm]		1.09	±	0.01	1.38	±	0.01	**
Surface	MIU: Mean coefficient of friction [-]	wale	0.222	±	0.003	0.378	±	0.003	**
		course	0.298	±	0.005	0.373	±	0.013	**
	MMD: Mean deviation of friction [-]	wale	0.010	±	0.001	0.011	±	0.001	**
		course	0.043	±	0.004	0.015	±	0.001	**
	SMD: Geometrical roughness [micron]	wale	4.85	±	0.28	6.87	±	0.22	**
		course	15.31	±	0.38	15.55	±	0.97	
Thermal transport	q-max [W/m^2]		824	±	13	678	±	4	**
	Thermal conductivity [W/(m・K)]		0.0604	±	0.001	0.0664	±	0.000	**
	Insulation rate [%]		24.7	±	1.3	30.3	±	0.4	**
Moisture transport	Wicking ＆ Quick drying [%]		26.5	±	4.0	19.3	±	2.5	*
Air permeability	Air flow resistance [KPa・s/m]		0.041	±	0.002	0.035	±	0.001	**
	Weight [g/m^2]		157.2	±	2.1	164.8	±	3.0	**

PET/PP had characteristics of a low dynamic friction coefficient (MIU) and low surface roughness (SMD). PET/PP had significantly lower thermal conductivity than PET/PET, even though q-max of PET/PP was higher. In addition, because the value of the wicking and drying rate was larger, PET/PP had higher moisture transfer from the skin surface to the outside.

PET/PET was a bulky and easily compressed sample with larger thickness and weight values. So, the value of insulation rate was also higher, and the sample had relatively better insulation property.

Table 2.4 shows the range of material property values of the samples used in this study and the previous studies which conducted wearing experiments. In the previous study [23], the thermal conductivity was significantly different (thermal conductivity; 0.0596 - 0.0783 [W/(m･K)]). In addition, the wicking and drying rates of the previous study was about twice that of 20.0 to 11.8 [%]. There were larger differences than the ranges of samples in this study.

There was also a significant difference in the value of air flow resistance this time, but the difference is not larger than existing studies. In the sample used in other previous research [42], the value of the air flow resistance was about twice as different (0.041- 0.084 [kPa·s/m]), so there was a difference in the sensation of stuffiness.

The two samples used in this study showed some significant differences between the samples due to the small variance of the measured data, but it is considered that the samples do not have absolute large differences compared to other similar wearing experiment studies.

Table 2.4. Ranges of material property values of the samples used in this time and the previous studies

Material properties		Samples in this study			Samples in previous studies		
Thermal transport	Thermal conductivity [W/(m・K)]	0.0604	~	0.0664	0.0596	~	0.0783
	Insulation rate [%]	24.7	~	30.3	20.9	~	29.3
Moisture transport	Wicking ＆ Quick drying [%]	19.3	~	26.5	11.8	~	20.0
Air permeability	Air flow resistance [KPa・s/m]	0.035	~	0.041	0.041	~	0.084

2.2.3 Wearing experiment

Wearing experiment was performed to evaluate the psychophysiological responses of participants wearing two types of undershirt sample having different characteristics.

Ten healthy male college students participated in the experiment (age: 21.8 ± 0.8 years, height: 173.7 ± 7.2 cm, mass: 64.2 ± 4.8 kg, body mass index: 21.3 ± 1.6). Due to a more stable body temperature and less changes in hormonal balance, male participants were chosen over female participants [43-45]. Also, participants were only healthy college students who had experience in the sensory evaluations and had discriminatory ability. The participants were advised to refrain from eating food for 2 hours before the experiment, from consuming alcohol for 24 hours before the experiment, and from consuming caffeine on the day of the experiment [46]. Each participant followed the experimental procedures for one sample per day, taking 2 days in total to complete the experiment. The information on the sample when worn was not given to the participants. A new undershirt sample was used in each experiment to avoid changing material properties of the samples. The experiment was carried out at the same time of day in consideration of the circadian rhythm of humans, to avoid potential bias resulting from the influence of thermoregulation [47].

The participants first changed clothes, putting on a T-shirt (100% cotton) and bottoms (cotton 54% and polyester 46%) to ensure the same initial state. The participants then entered a room with a constant temperature and relative humidity of 20 °C and 65% respectively, and rested for 15 min to allow their bodies to adjust to the temperature. ECG electrodes were then attached to the participants' skin. The ECG was attached via a bipolar chest lead and the signal was amplified by an amplifier. Temperature and humidity sensor electrodes were also attached to four parts of the body (i.e., the left side of the chest, the abdomen, the upper back, and the lower back) to measure the mean skin surface temperature and the mean humidity within the clothes. These sensors recorded the temperature conducted inside the main body. Humidity is detected by the humidity sensor inside the vent with a diameter of 1.27 mm on the surface of the sensor. These sensors were attached to the skin surface with the vents facing outward to measure the humidity of the microclimate between clothing and the skin. A pulse measurement transducer (TSD200-MRI; BIOPAC Systems, Inc.) was attached to each participant's right index finger, and the transducer was amplified by a PPG100C amplifier (BIOPAC Systems, Inc.) to measure the finger plethysmogram. The location of these sensors attached to the body is shown in Figure 2.3.

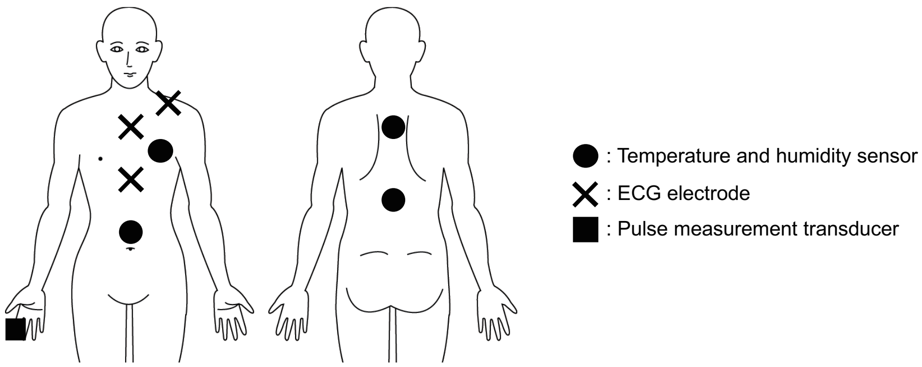


Figure 2.3. The position of the attached sensors

After the attaching sensors and taking 15 min for pre-rest, each participant randomly wore one of the two sample undershirts. The experiment took 60 min in total (Figure 2.4). Each participant first rested for 20 min and then exercised on an aero bike (75XLIII; Konami Sports Life Co., Ltd., Kanagawa, Japan) for 10 min at an intensity of 55%–65% of their maximum heart rate [bpm], calculated using the expression "220 – age in years". The maximum heart rate value was taken as a guide to moderate aerobic exercise in daily life.[48] After the exercising, participants rested again for 30 min.

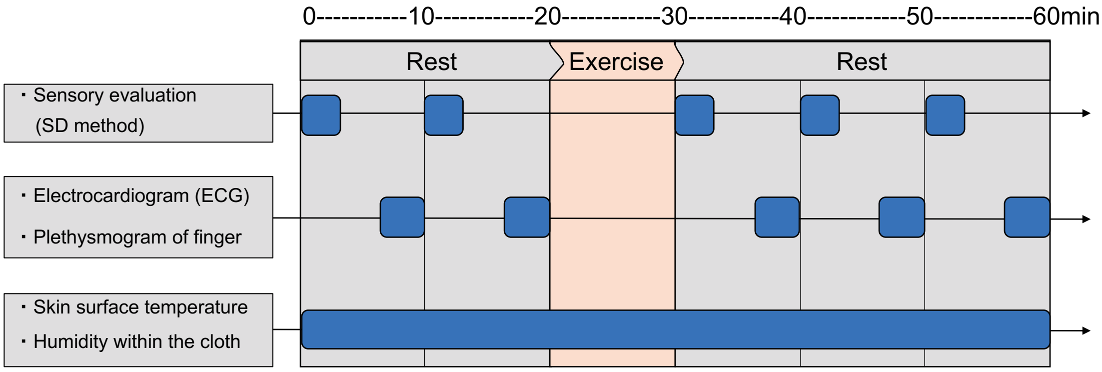


Figure 2.4. Experimental protocol–

During the 60-min duration of the experiment, the participant's physiological and psychological responses were measured to evaluate the comfort sensation when the two sample undershirts were worn and to investigate the autonomic nervous activities of the participant.

The semantic differential (SD) method was employed for psychological measurements. The sensations felt by the participants were measured five times in total at intervals of 10 min, except while exercising. There were nine evaluation term pairs: Hot–Cool, Sticky–Slippery, Stuffy–Dry, Rough–Smooth, Hard–Soft, Heavy–Light, Thick–Thin, Poor texture–Good texture, and Uncomfortable–Comfortable (Table 2.5). The evaluation scale comprised seven levels (i.e., extremely, very, slightly, neither, slightly, very, and extremely), and a score of −3 to +3 was given to quantify the evaluation. These evaluation term pairs were selected with reference to those used in previous studies of a wearing experiment [23]. The evaluation term pair of Stuffy– Dry was selected to measure the thermal discomfort caused by changes in thermal, moisture, and air permeability caused by exercise and perspiration. "Stuffy" translates as "Mure" in Japanese. Poor texture–Good texture is the total contact sensation felt by the contact between the skin surface and fabrics.

Table 2.5. Evaluation term pairs of SD method

Evaluation term pairs
Hot–Cool
Sticky–Slippery
Stuffy–Dry
Rough–Smooth
Hard–Soft
Heavy–Light
Thick–Thin
Poor texture–Good texture
Uncomfortable–Comfortable

Temperature and humidity sensors were used to measure the mean skin surface temperature and the mean humidity within the clothing throughout the 60-min experiment as the thermophysical indices. The average value of the temperature at the four points of the upper body (i.e., the chest, abdomen, upper back, and lower back) was calculated as the skin surface temperature. Similarly, the average value of the humidity at the four points of the upper body was calculated as the humidity within the clothing.

As a method of physiological measurement, to measure the activity of the autonomic nervous system, ECG signals and a finger plethysmogram were recorded a total of five times at intervals of 2 min. The above signals were sampled at a frequency of 2000 Hz. The results from the ECG were analyzed to calculate some indices of autonomic activity. The results of the ECG—which measures autonomic nervous system activity—were analyzed. The time-series data pertaining to the time between adjacent R waves (i.e., the R–R interval) were obtained. CVRR was calculated using the coefficient of variation (CV) of the value of the R–R interval for each period of 2 min. The CVRR expresses the fluctuation of the heartbeat, with a higher value indicating an increase in parasympathetic nervous activity [49]. In addition, Using R–R interval values, spline interpolation was performed. The integral ratio of the spline curve from the fast Fourier transform analysis was obtained by dividing the integral of low frequency (LF) (0.04–0.15 Hz) by the integral of high frequency (HF) (0.15–0.40 Hz) on the power spectrum. LF/HF was calculated as the ratio of LF and HF. LF/HF is a sympathetic nervous activity index, and the stress experienced is considered to increase with the value of the index [50]. MATLAB (MathWorks, Inc., Natick, Massachusetts, USA) was used for the analysis.

In addition to the ECG, other autonomic nervous system activity indexes were used from a finger plethysmogram. The rising point during each beat was calculated from the pulse wave obtained by the pulse measurement transducer. The time difference between the value of the pulsation and the R wave of the electrocardiogram was obtained, and the pulse transit time (PTT) was calculated. The PTT is negatively correlated with blood pressure because the pulse wave transit time becomes shorter with vasoconstriction, and it was measured as an index of the blood pressure fluctuation. MATLAB software was also used in the analysis.

A two-way ANOVA was performed on the values of sensory evaluation and thermophysical indices every 10 min with two factors (i.e., the sample and time). There were two levels of sample (i.e., PET/PP, and PET/PET) for all indices. There were seven levels of time (i.e., 0, 10, 20, 30, 40, 50, and 60 min) for each thermophysical index, and five levels of time (i.e., 0, 10, 30, 40, and 50 min) for each sensory evaluation score.

2.3 Results

2.3.1 Physical conditions of the wearing state

Results of the thermophysical responses of wearers due to changes in the pre-resting, exercise, and post-resting process are first described. Figure 2.5 shows the mean skin surface temperatures. The values are means for the 10 participants. As the result of a two-way ANOVA, there was a significant main effect of time, $F(6, 54) = 13.65$, $p < .001$. The main effect of sample was non-significant, $F(1, 9) = 3.03$, $p = 0.12$, nor was the interaction between time and sample, $F(6, 54) = 0.27$, $p = 0.95$. The temperatures of wearing both samples increased for 10 min from the start, and decreased after exercise.

Multiple comparisons revealed that there were significant differences between the samples in all time (**$p < 0.01$, *$p < 0.05$). The value for PET/PP was consistently larger than that for PET/PET over the 60 min of the experiment.

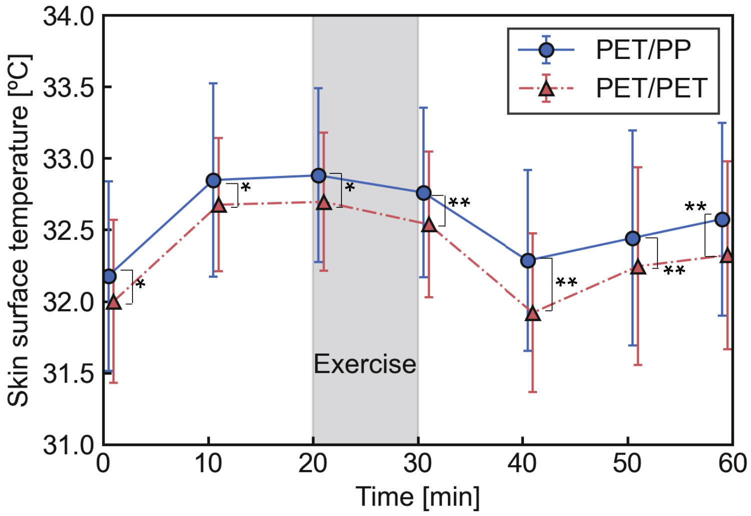


Figure 2.5. Mean skin surface temperature over time (**$p < 0.01$, *$p < 0.05$)

Table 2.6 denotes the calculated difference between the maximum temperature before exercise and the minimum temperature after exercise. The temperatures decreased after exercise for both samples. The differences between the maximum temperature before exercise and the minimum temperature after exercise was 0.63 ºC for PET/PP and 0.83 ºC for PET/PET. The skin surface got colder after exercise when wearing PET/PET.

Table 2.6. The maximum and minimum mean skin surface temperature and their differences

Temperature [℃]	Maximum		Minimum		Difference
PET/PP	32.91	(23min)	32.29	(40min)	0.63
PET/PET	32.74	(18min)	31.91	(39min)	0.83

Figure 2.6 gives the average humidity within the clothing for 10 participants over the course of the experiment. As the result of a two-way ANOVA, there was a significant main effect of time, $F(6, 54) = 31.43$, $p < .001$. The main effect of sample was non-significant, $F(1, 9) = 0.91$, $p = 0.36$, nor was the interaction between time and sample, $F(6, 54) = 1.08$, $p = 0.38$. For both samples, the humidity suddenly increased immediately after exercise. Afterward, the humidity dropped to a neutral level.

It was confirmed that the participants perspired because of exercise in the experiments. The perspiration generated a physical stimulus including a decrease in the skin surface temperature and a rapid increase in humidity within the clothes after exercise.

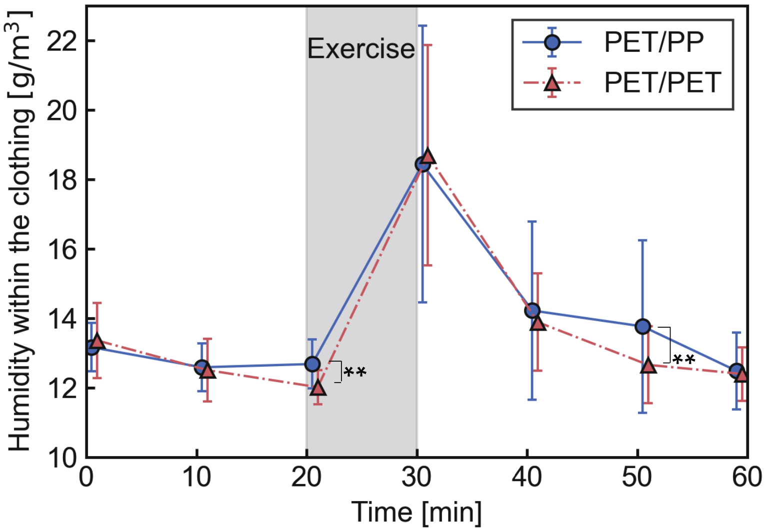


Figure 2.6. Mean humidity within the clothing over time (**$p < 0.01$, *$p < 0.05$)

2.3.2 Psychological sensations

(a) Changes in the exercise/rest process

Results of the psychological sensations due to changes in the pre-resting, exercise, and post-resting process are first described.

Average values and standard deviations of the data obtained for all evaluation term pairs in the SD method were calculated for each of the ten participants. Figure 2.7 denotes the average values of the evaluation terms at each time. A larger value indicates a more positive (comfortable) impression.

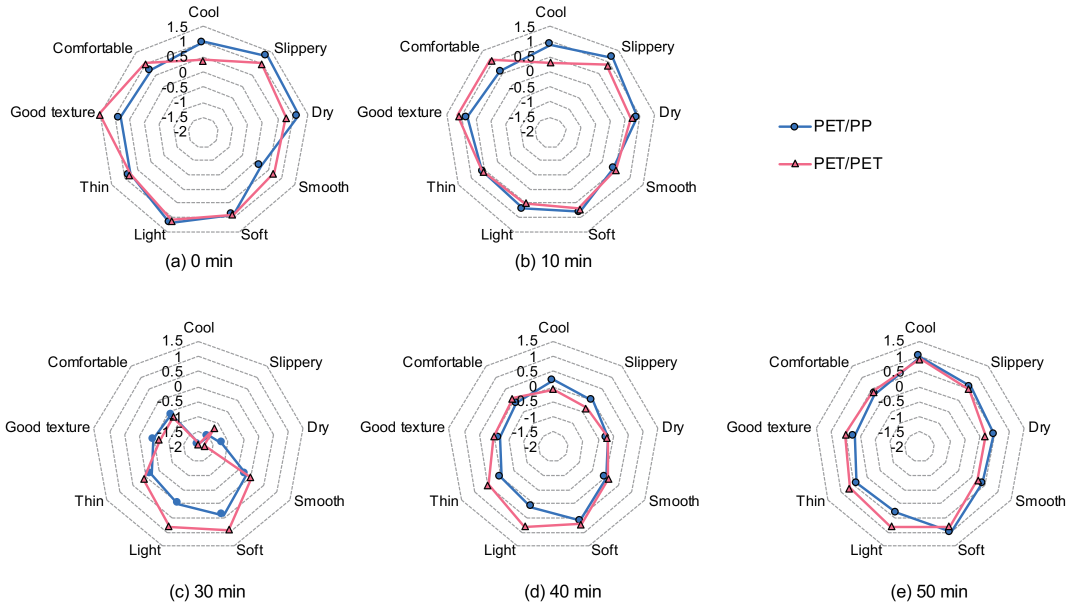


Figure 2.7. Average values of the evaluation terms at each time; (a) at 0 min, (b) at 10 min, (c) at 30 min (after exercise immediately), (d) at 40 min, (e) at 50 min–

Evaluation values presented in Figure 2.7(c) for the time after exercise were smaller than those presented in the pre-rest time (Figure 2.7(a) and (b)). The psychological impression also changed significantly before and after exercise as in physical conditions, the skin surface temperature and the humidity within the clothing.

As the results of two-way ANOVA in each evaluation term, there were significant main effects of time for all evaluation terms except for Rough-Smooth and Hard-Soft ($p < .001$). There was no interaction between time and sample for any term pair. When wearers perspired after exercise, the roughness and hardness sensations of the undershirts did not change significantly. However, sensations of discomfort, such as hot, stuffy, and sticky sensation were greatly strengthened by exercise and perspiration. Following these sensations, the overall sensations of texture and comfort also worse than before exercise.

Table 2.7. Results of two-way ANOVA for all evaluation terms (**$p < 0.01$, *$p < 0.05$)

Evaluation term pairs	Effect of time			Effect of sample			Interaction	
	$F(4,36)$	p		$F(1,9)$	p		$F(4,36)$	p
Hot-Cool	30.44	0.00	**	7.11	0.03	*	1.09	0.36
Sticky-Slippery	16.89	0.00	**	1.16	0.31		1.13	0.36
Stuffy-Dry	17.98	0.00	**	6.23	0.03	*	1.00	0.41
Poor texture-Good texture	13.68	0.00	**	1.01	0.34		1.05	0.40
Rough-Smooth	2.07	0.13		0.43	0.53		0.98	0.41
Hard-Soft	0.98	0.43		0.08	0.79		1.16	0.34
Heavy-Light	6.57	0.00	**	3.82	0.08		2.64	0.07
Thick-Thin	7.03	0.00	**	0.93	0.36		0.88	0.49
Uncomfortable-Comfortable	9.15	0.00	**	1.41	0.27		0.78	0.55

A multiple regression analysis was performed to investigate psychological factors related to the clothing comfort sensation in this experiment. The Uncomfortable–Comfortable pair was used as objective variables, and the remaining evaluation terms were adopted as explanatory variables using the data of all time zones. The analysis adopted the stepwise method. As a result, Stuffy–Dry, Poor texture–Good texture, Rough–Smooth, and Thick–Thin were selected as explanatory variables shown in Table 2.8. These evaluation terms except Thick–Thin were significant variables (p < 0.05). Focusing on the standard partial regression coefficients, the scores of the stuffy sensation and skin texture sensation were high, and these sensations greatly affected the clothing comfort sensation in the process of pre-rest, exercise, and post-rest.

Table 2.8. Results of multiple regression analysis for all data

Objective variable	Explanatory variable	Partial regression coefficient	Standard error	Standardized partial regression coefficient	*F* value	*t* value	*p* value	
Uncomfortable–Comfortable (Adjusted R^2 = 0.74)	Stuffy-Dry	0.38	0.06	0.46	41.07	6.41	0.00	**
	Poor texture-Good texture	0.41	0.07	0.44	31.17	5.58	0.00	**
	Rough-Smooth	0.17	0.07	0.16	6.84	2.61	0.01	*
	Thick-Thin	-0.10	0.06	-0.09	2.42	-1.56	0.12	
	Constant term	0.10	0.06	-	2.83	1.68	0.10	

**: p<0.01, *: p<0.05

Factor analysis was performed for all nine evaluation terms except Uncomfortable–Comfortable, to identify the potential psychological factors that participants mainly felt in the exercise/rest process. The software R was used in the analysis. Results are shown in Table 2.9. The number of factors was set to three because there were three factors with eigenvalues of 1.0 or more. Promax rotation was performed.

The contribution ratio of factor 1 was 32.3%. The explanatory variables with a large factor loading were Hot–Cool, Sticky–Slippery, and Stuffy–Dry sensations. Factor 1 thus reflects a sensation related to the thermal and moisture transport characteristics of fabrics. Explanatory variables with large factor loadings of factor 2 were Poor texture–Good texture, Rough–Smooth, and Hard–Soft. Factor 2 thus reflected a sensation related to the texture sensation felt when touching fabrics. The explanatory variables with a large factor loading of factor 3 were Heavy–Light and Thick–Thin. Factor 3 thus reflected a physical sensation of the fabric itself.

Factor analysis revealed that the three main potential factors were the sensation of thermal and moisture transport characteristics, the sensation of the skin texture, and the physical sensation of the skin in the exercise/rest process.

Table 2.9. Results of factor analysis

Evaluation terms	Loadings		
	Factor 1	Factor 2	Factor 3
Hot–Cool	0.74	-0.07	0.19
Sticky–Slippery	0.88	0.00	0.10
Stuffy–Dry	0.97	0.00	-0.05
Poor texture–Good texture	0.54	0.55	-0.16
Rough–Smooth	-0.05	0.78	-0.04
Hard–Soft	-0.18	0.66	0.17
Heavy–Light	0.05	0.05	0.70
Thick–Thin	0.02	-0.04	0.82
Loadings (sum of squares)	2.58	1.36	1.27
Proportion of Variance [%]	32.3	17.0	15.9
Cumulative Proportion [%]	32.3	49.3	65.2

(b) Differences between samples

The scores at each moment in time did not change as largely between samples as between processes. However, two-way ANOVA showed the main effects of samples were significant for the terms of Hot-Cool and Stuffy-Dry ($p < .05$) as seen in Table 2.7. Significant differences were confirmed between the samples with sensations of thermal and moisture transport properties.

Figures 2.8 and 2.9 show the Hot–Cool and Stuffy–Dry scores over time, respectively. Regarding the scores of Hot–Cool, a large difference was observed between the samples at pre-rest (0 min and 10 min). Tukey's multiple comparison test showed a significant difference of 1% between samples at 0, 10, and 40 min from the start of the experiment. The values of PET/PP were higher than those of PET/PET at these times.

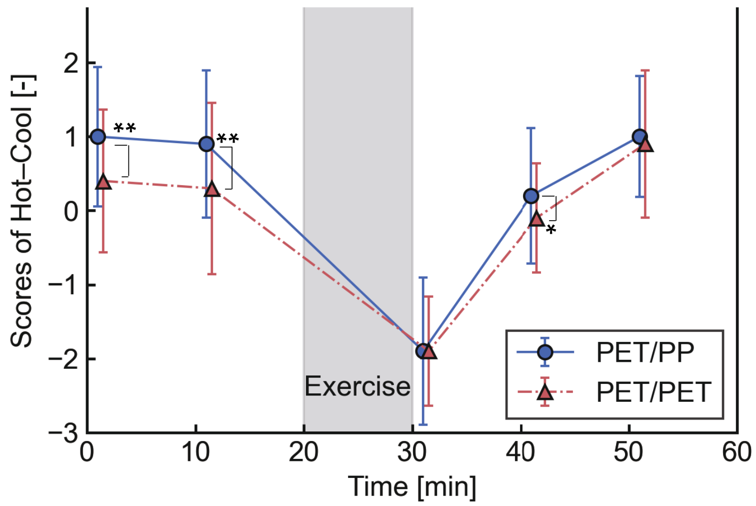


Figure 2.8. Sensory evaluation scores of Hot–Cool between samples over time

(**$p < 0.01$, *$p < 0.05$)–

Regarding the scores of the sensory evaluation Stuffy–Dry, multiple comparisons made adopting Tukey’s test revealed a significant difference between scores for the samples at 0, 30, and 50 min. At these times, the values for PET/PP were higher than the values for PET/PET. In particular, a large difference was observed between the samples immediately after exercise (30 min). It was found that the stuffy sensation of PET/PP was weaker.

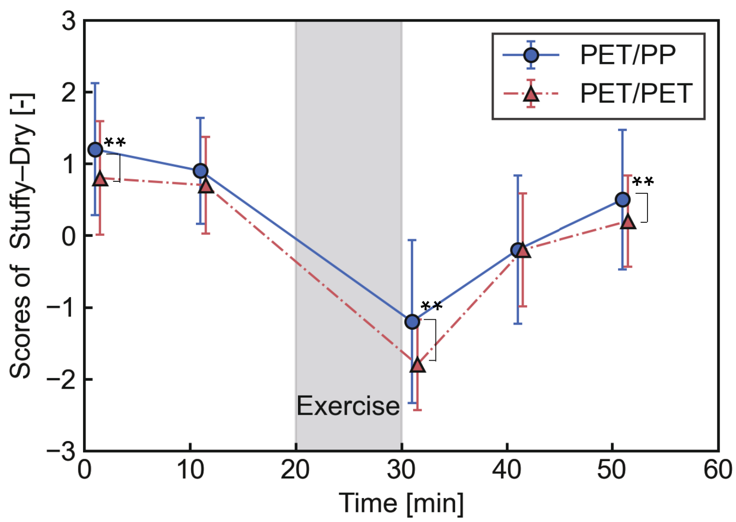


Figure 2.9. Sensory evaluation scores of Stuffy–Dry between samples over time (**$p < 0.01$, *$p < 0.05$)

2.3.3 Autonomic nervous activity indices

To evaluate the physiological condition of humans when worn the samples, the average values of CVRR and LF/HF for each sample obtained from the ECG, and PTT obtained from the finger plethysmogram were calculated. These are autonomic nervous activity indices.

Figure 2.10 shows the average values and standard deviations of CVRR calculated from 10 participants. Multiple comparison s made adopting Tukey's test revealed significantly higher values of the CVRR for PET/PP than for PET/PET at 38-40 min and 58-60 min ($p < 0.01$). The activity of parasympathetic nervous predominantly enhanced when wearing PET/PP than when wearing PET/PET.

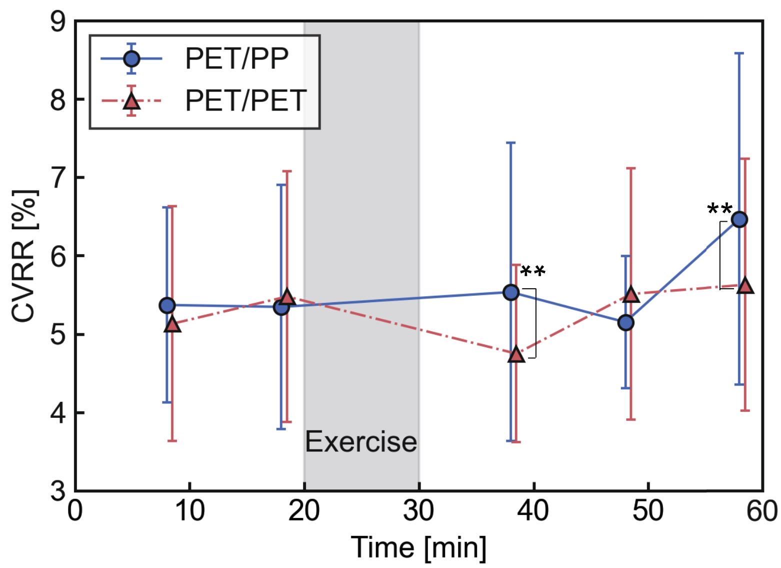
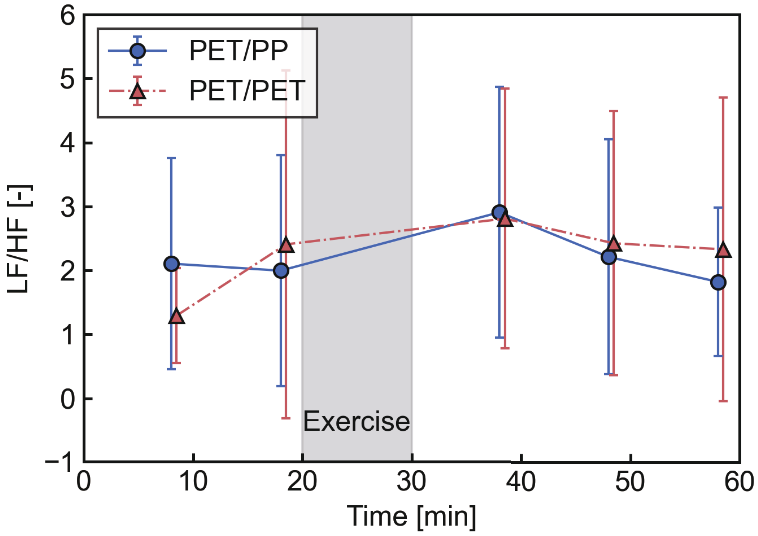


Figure 2.10. CVRR scores between samples over time (**$p < 0.01$, *$p < 0.05$)–

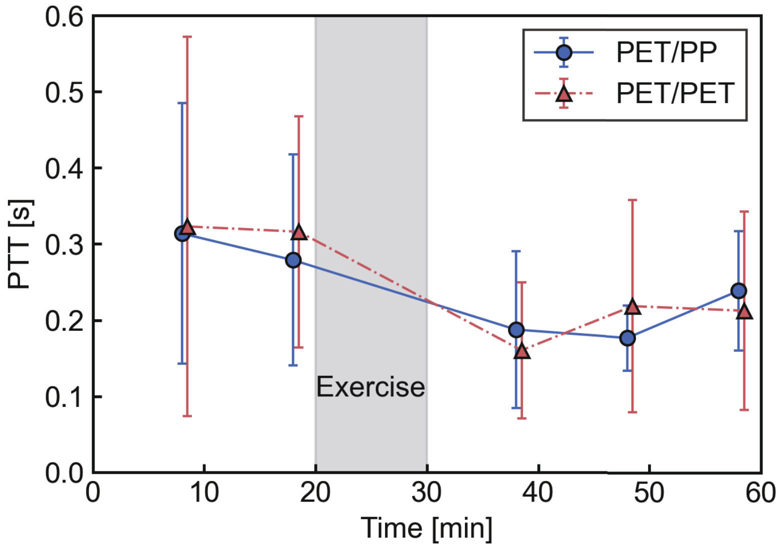
Regarding the values of LF/HF, there were three outliers that were much higher than the average value of all data (> Mean + 3SD). The values were 13.4 at 38-40 min for PET/PP, 11.0

at 58-60 min for PET/PP and 11.3 at 58-60 min for PET/PET. Therefore, the averages value and standard deviations of 9 participants were used for these times of each sample for LF/HF. For LF/HF, we performed Mann-Whitney U-test between samples at each time because some outliers were excluded, and the numbers of data were not equal in the samples at some conditions. Figure 2.11 shows the average values of LF/HF over time. As the result of Mann-Whitney U-test, there were no significant differences in LF/HF between samples in each time. Although the variance was large, LF/HF tended to increase for both samples at the measurement after exercise, then sympathetic activity tended to predominate.



5)–

Figure 2.12 shows the average values of PTT over time. As results of multiple comparisons, there was no significant difference between samples in each time. There were no outliers like LF/HF, but there were some participants with high absolute values. The value of PTT tended to decrease at after exercise in the time process.



In the physiological indices in this study, a significant difference was confirmed between the samples in the parasympathetic nervous system activity index, but no significant difference was confirmed in the sympathetic nervous system activity index.

2.3.4 Relationships between psychological sensations and the autonomic nervous activity index

To investigate the relationships between the clothing comfort sensation and autonomic nervous system activity, correlation analysis was performed using average values for 10 participants, for each sample at 10, 40, and 50 min, at which time there were data for all measurement indices. High negative correlation ($r < -0.97$, $p < 0.01$) was found between LF/HF obtained from the ECG and the psychological values of the Uncomfortable–Comfortable evaluation as shown in Figure 2.13.

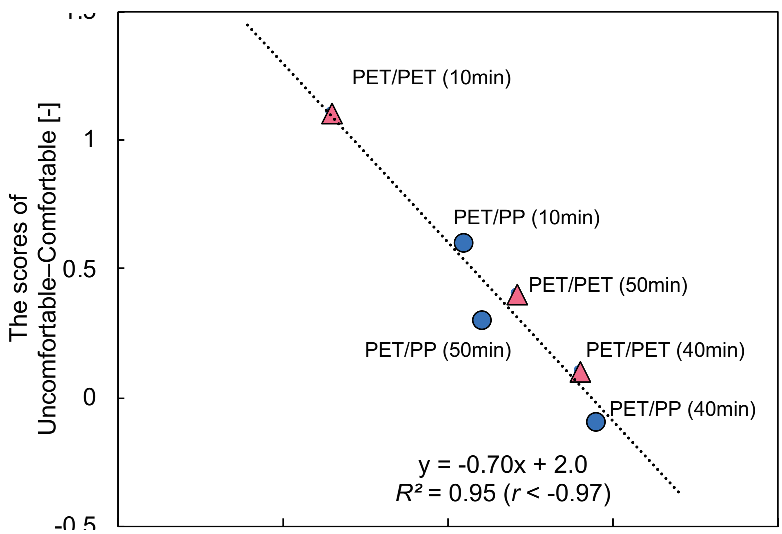


Figure 2.13. Relationship between LF/HF values and the psychological scores of Uncomfortable–Comfortable

Figure 2.14 shows the results of the psychological scores of Stuffy–Dry after exercise and the CVRR score, which were significantly different between samples. There was a significant difference in the stuffy sensation immediately after exercise and at the time of the last measurement, and the values of PET/PET were lower, indicating a stuffier sensation.

The CVRR value for the PET/PET sample was smaller after exercise and at the time of the last measurement. This suggested that the CVRR was greater when the stuffy sensation was weaker. Additionally, Figure 2.15 shows a scatter plot of the scores of stuffy sensations and CVRR values in Figure 2.14. The regression line and the regression curve were also plotted on the figure. In this figure, the relationship between the sensation of stuffiness and CVRR was more suitable for the quadratic curve rather than the simple linear relationship. The significant difference in Figure 2.14 suggested that there was a corresponding relationship between stuffiness and CVRR, but it was indicated that the relationship was not a simple linear relationship.

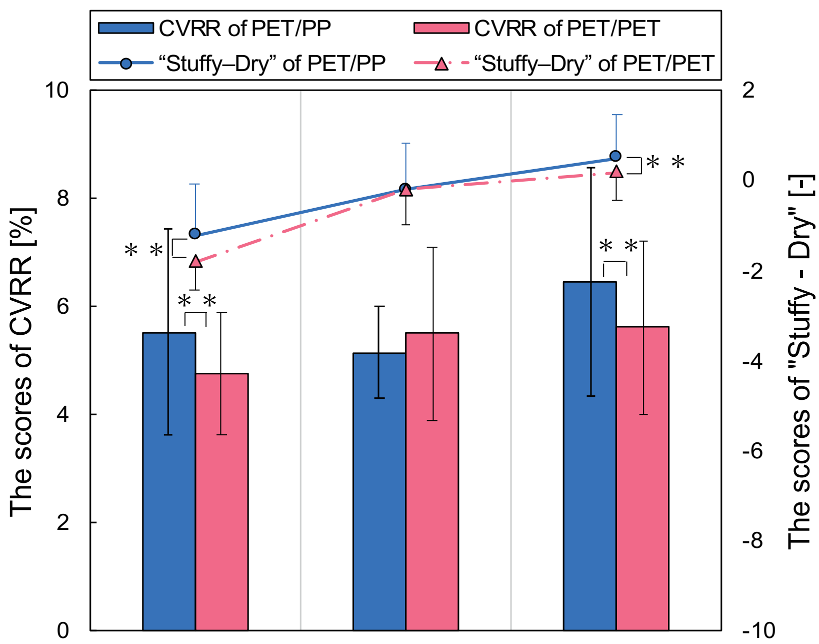


Figure 2.14. Relationship between CVRR values and the psychological scores of Stuffy–Dry (**$p < 0.01$, *$p < 0.05$)–

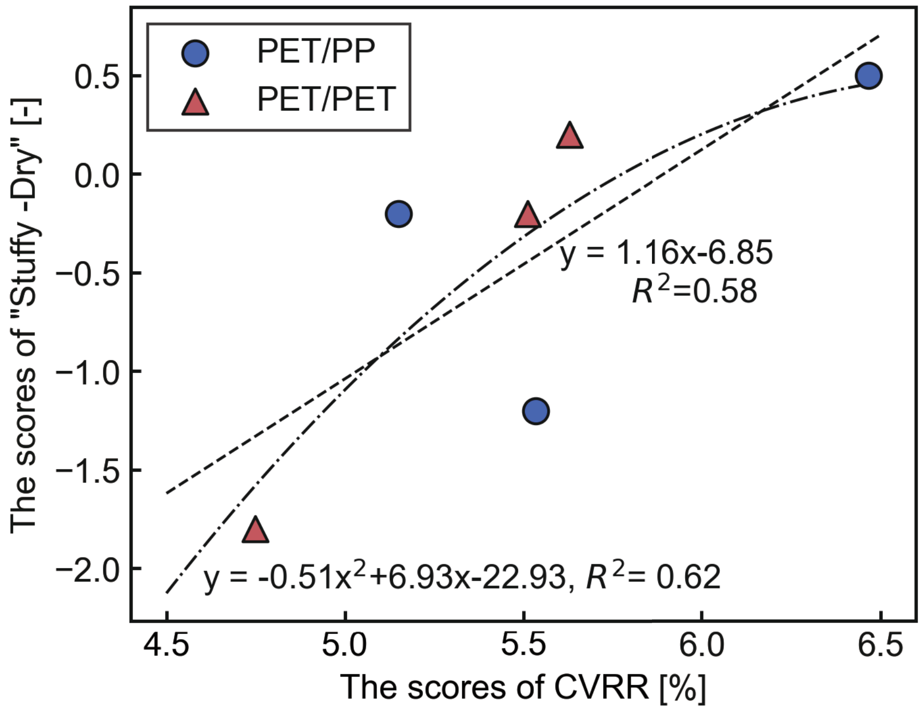


Figure 2.15. Scatter plot of CVRR values and the psychological scores of Stuffy–Dry, and regression line and regression curve

2.4 Discussion

2.4.1 Physical conditions of the wearing state

A drastic increase in humidity within the clothes due to exercise was observed around 30 min as seen in Figure 2.6. This result indicates that the participants perspired immediately after exercise. There was no significant difference in the humidity within the clothes and thus no difference in the degree of perspiration between samples. After the perspiration (at 40 min), a decrease in skin surface temperature due to a sweat chill was observed for both samples (Figure 2.5 and Table 2.5). Although there was no difference in humidity within the clothes, there was a difference in the temperature reduction between the samples. The result was considered to relate to the moisture transport property of the fabric samples. The temperature drop of PET/PP was smaller because the sample had a significantly higher wicking and quick drying property (Table 2.3). The moisture on the skin surface was considered to move to the outside quickly, and it was difficult to chill the skin surface.

2.4.2 Psychological sensations

Two-way ANOVA in the sensory evaluation revealed significant differences in the factor of sample only for Hot–Cool and Stuffy–Dry (Table 2.6). The result was considered to be due to thermal and moisture transport properties. There were significant differences in the thermal sensation Hot–Cool between the samples at the pre-rest time. The values of thermal transport properties (q-max and insulation rate) of the samples were thought to relate to this result. It had been recognized that q-max correlates with human contact coolness. PET/PP with a larger value of q-max provided a cool sensation. Additionally, the higher insulation rate of PET/PET also led to the warm sensation of PET/PET.

Significant differences in the scores of Stuffy–Dry were observed between samples after exercise (at 30 and 50 min). The values for PET/PP were higher than those for PET/PET. The stuffy sensation was weaker for PET/PP. This result might be explained by the thermal and moisture transport properties and surface properties of fabrics being related. The sensation of stuffiness is a complex factor of the sensations of warmth and touch.[51] PET/PP had a high q-max, which means a stronger contact cooling sensation, and a lower dynamic friction coefficient (MIU) and small surface irregularity (SMD of wale direction) significantly, and easy to remove moisture on the skin surface because of the wicking and drying rates of the moisture transport properties. This may have weakened the sensation of stuffiness, even though the material properties of samples were subtle differences.

2.4.3 Autonomic nervous activity indices

LF/HF, which is the sympathetic nervous activity index, increased at the measurement after exercise. These changes correspond to the result that the clothing comfort sensation changed significantly in the exercise/rest process. There was high correlation between the clothing comfort sensation and LH/HF values in the time process. This result indicated that LF/HF is useful in estimating clothing comfort sensation in situations involving dynamic change, such as the pre-rest, exercise, and post-rest process. This result was same tendency as the results of previous literatures in that the stress of the sensation of skin touching and thermal sensation when wearing clothing enhance the sympathetic nervous activity [22, 23, 52, 53]. However, there was no significant difference between samples due to the large variability among participants. It was not possible to capture the subtle differences in material characteristics of the samples using LF/HF at in this chapter.

The differences between samples might affect the CVRR when the participants felt the psychological stuffy sensation (Figure 2.14). The stuffy sensation might be generated by the thermal stimulus of perspiration due to exercise and the effect of moisture as mentioned in the discussion above. It was possible that such a complex thermal discomfort sensation can be estimated using the CVRR. A previous study reported that the CVRR is significantly higher when wearing work wear with a fan to prevent heat stroke than when wearing work wear without a fan.[54] The CVRR is therefore an index of comfort related to stuffiness and thermal stimulus. At this time, it was considered that the CVRR was higher for PET/PP because of better management of thermal and moisture after perspiration. It was considered that the difference in thermal and moisture transport properties of the undershirt samples was reflected in the parasympathetic nervous activity of the participants. However, Figure 2.15 indicated that the relationships of absolute values of CVRR and stuffy sensations were not simple linear. It was suggested that fitting the relationship between physiological and psychological values using a simple linear analysis was not always suitable. Performing non-linear analyzes such as quadratic curves may be more effective in showing complex psychological factors.

Significant differences were observed between samples in terms of Hot–Cool and Stuffy–Dry (Table 2.6) due to the stimulation in this experiment, which was thermal changes such as body temperature rise and perspiration due to exercise. It was considered that CVRR, which is the parasympathetic nervous system index, can be used to evaluate the differences in the physical conditions and psychological responses related to different thermal changes in the samples, rather than the sympathetic nervous system activity indices like LF/HF and PTT.

2.5 Summary

In this chapter, the two kinds of undershirts with small differences in material properties were constructed from two types of fiber materials with similar characteristics (PP and PET) to investigate the effectiveness of psychophysiological response measurement for the evaluation of clothing comfort sensation. The wearers' psychological sensations and physiological responses, such as ECG and pulse, were measured during pre-rest, exercise, and rest.

As a result, it was found that the humidity within the clothing increased sharply, and the skin surface temperature decreased because of perspiration after exercise. Regarding psychological sensations, the sensation of stuffiness increased, and discomfort increased after exercise. In the exercise and rest periods, the LF/HF index values obtained using ECG exhibited a strong negative correlation with clothing comfort sensation. The results suggested that it is possible to estimate discomfort during perspiration caused by exercise from LF/HF. However, the differences between the samples were not confirmed in the LF/HF results.

Wearers identified differences between the samples in the sensation of coolness and stuffiness, discriminating the minute differences between the thermal and moisture transport properties of the samples. In addition, the difference in the sensation of stuffiness between the samples after exercise was consistent with the CVRR obtained from the ECG, which is an index of parasympathetic nervous system activity. This finding suggests that CVRR can be used to estimate complex discomfort, such as the sensation of stuffiness associated with thermal and moisture transport properties. Therefore, the measurement of psychophysiological responses and conventional linear analysis methods could be applied in some components of evaluation of clothing comfort sensation when wearing clothing with minute material differences. However, the relationship between CVRR and the sensation of stuffiness did not exhibit a strong linear relationship. Thus, using non-linear analysis may be a more suitable approach for the evaluation of complex psychological factors, such as the sensation of stuffiness.

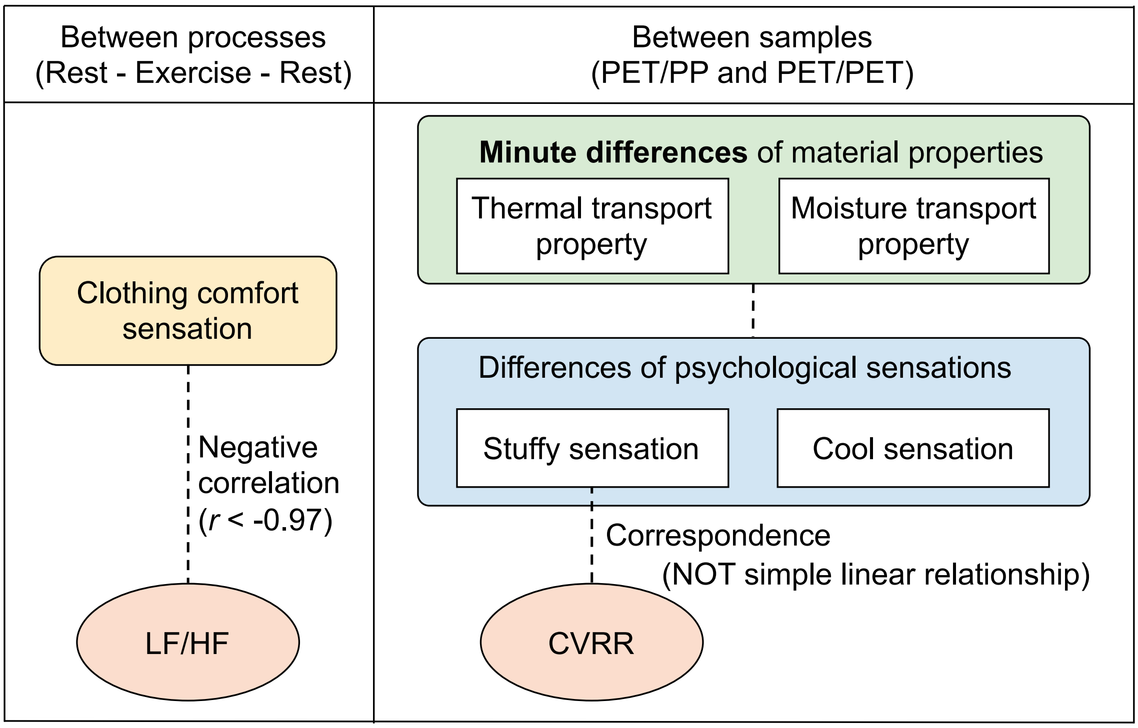


Figure 2.15. Summary of the results of Chapter 2–

Chapter 3. Psychophysiological data collection for ANN and analysis of the data structures

3.1 Introduction

In Chapter 2, some relationships between psychophysiological indices were clarified using conventional analysis methods, and the evaluation of clothing comfort sensation was verified. In Chapter 3, the proposed ANN analysis was examined as a method for evaluating clothing comfort sensation. First, this chapter describes the details of an experiment designed to collect data required for the ANN analysis described in Chapter 4. The tendencies in the data were then analyzed for the latter part of the ANN analysis.

3.2 Methods

3.2.1 Materials

For the purpose of preparing various types of data in later wearing experiments for ANN, three types of blended yarns containing both hydrophobic fibers and hydrophilic fibers were selected in order to change the thermal and moisture coupling of the sample. Table 3.1 provides the blending ratios and properties of the spun yarns. Cotton, rayon, and PP were used to prepare blended yarns of cotton and PP (PP/Cy) and of rayon and PP (PP/Ry). The blending ratio of hydrophilic fibers to hydrophobic (PP) fibers was 70:30. This ratio was similar to the value considered suitable for favorable moisture transfer characteristics based on previous research [55].

Table 3.1. Blending ratios of the yarns and specifications of the spun yarns (means ± SDs)

Yarn	Blending ratio [%]	Fineness of yarn [tex]	Diameter [μm]	Number of twists [time/inch]	Twist factor [-]	Tensile strength [N/tex]
PP/Ry	Rayon 70% / PP 30%	13.8 ± 0.7	162 ± 6	25.3 ± 1.3	3.9 ± 0.3	1.23 ± 0.05
PP/Cy	Cotton 70% / PP 30%	14.9 ± 0.7	224 ± 16	24.6 ± 0.6	3.9 ± 0.2	1.24 ± 0.14
Cy	Cotton 100%	14.1 ± 0.3	257 ± 8	24.6 ± 0.8	3.8 ± 0.2	1.39 ± 0.29

Table 3.2 shows details of the fabric samples made from the spun yarns and the comprehensive mixing ratios of the samples. The fabric samples comprised rib stitches produced by a circular knitting machine (gauge number: 18), and were made so as to interknit two spun yarns (Figure 3.1). An offset needle bed, in which the front and rear needle banks were offset by half the width of the interval between the needles, was used to produce the fabrics. The three types of fabric samples are denoted PP/R/C (where R signifies rayon), PP/C (where C signifies cotton), and C. In all three samples, the yarns on the skin side of the fabric (skin side yarns) were

spun from cotton. The yarns on the face side of the fabric (face side yarns) differed depending on the sample. The face side yarns of the PP/R/C sample comprised PP/Ry (a blended yarn of rayon and PP), whereas the face side yarns of the PP/C sample comprised PP/Cy (a blended yarn of cotton and PP). The face side yarns of the C sample were Cy (a spun yarn of cotton).

Table 3.2. Total blend ratios and knitting properties of the fabric samples

Fabric sample	PP/R/C	PP/C	C
Skin side yarn	Cy (Cotton 100%)	Cy (Cotton 100%)	Cy (Cotton 100%)
Face side yarn	PP/Ry (Rayon 70% / PP 30%)	PP/Cy (Cotton 70% / PP 30%)	Cy (Cotton 100%)
Total blend ratio	Cotton 65% / Rayon 25% / PP 10%	Cotton 90% / PP 10%	Cotton 100%
Fabric thickness [mm]	1.22 ± 0.02	1.26 ± 0.01	1.31 ± 0.02
Mass per unit area [g/m^2]	144 ± 3	143 ± 5	157 ± 2
Stitch density of wale [/inch]	29.0 ± 0.0	29.2 ± 0.4	29.4 ± 0.5
Stitch density of course [/inch]	28.0 ± 0.0	26.2 ± 0.4	29.6 ± 0.5
Loop length of skin side yarn [mm]	3.3 ± 0.1	3.3 ± 0.0	3.0 ± 0.1
Loop length of face side yarn [mm]	2.6 ± 0.0	2.7 ± 0.0	2.5 ± 0.0
Cover factor [-]	1.28	1.28	1.36

Structure: Rib knitting, Diameter of knitting: 30", Number of needle: 2640, Gauge number: 18G

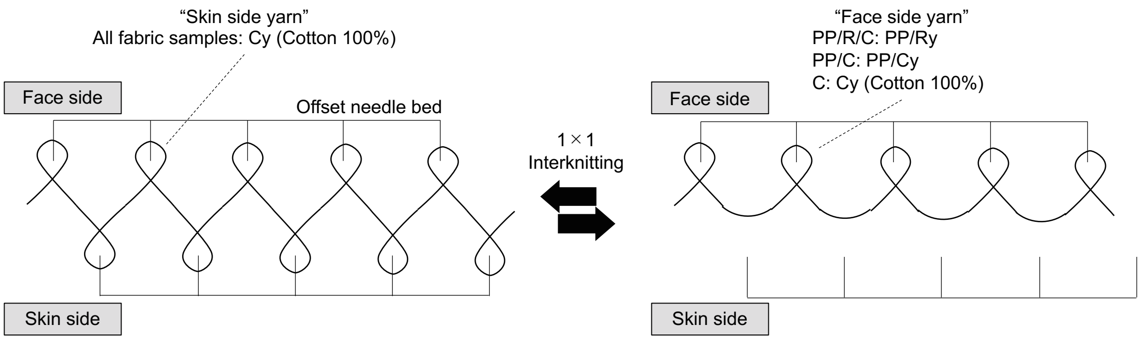


Figure 3.1. Manufacturing process of rib knitting

3.2.2 Material properties of samples

Table 3.3 shows the material properties of the fabrics. The measurement indices were the same as in Chapter 2, mechanical properties, thermal, moisture, and air transport properties. The environmental conditions at the time of measurement and the number of measurements were all the same as in Chapter 2.

Table 3.3. Mean values and standard deviations (SD) of the material properties of the fabric samples

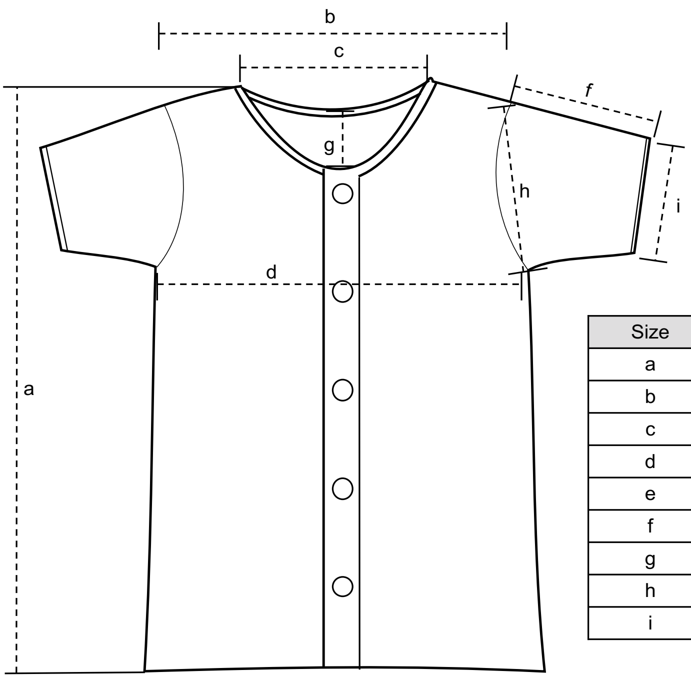
Blocked Property	Property		PP/R/C Mean ± SD	PP/C Mean ± SD	C Mean ± SD	Reference & Conditions of measurement
Bending	B: Bending rigidity [gf・cm²/cm]	wale	0.023 ± 0.001	0.027 ± 0.001	0.038 ± 0.002	KES-FB2 Maximum curvature : 2.5 [/cm]
		course	0.005 ± 0.001	0.008 ± 0.001	0.01 ± 0.002	
	2HB: Hysteresis of bending moment [gf・cm/cm]	wale	0.030 ± 0.001	0.037 ± 0.001	0.049 ± 0.002	
		course	0.005 ± 0.001	0.008 ± 0.000	0.011 ± 0.001	
Compression	LC: Linearity of compression-thickness curve [-]		0.31 ± 0.01	0.33 ± 0.00	0.32 ± 0.00	KES-FB3 Rate of compression : 50 [s/mm] Maximum Pressure : 50 [gf/cm²]
	WC: Compression Energy [gf・cm/cm²]		0.43 ± 0.03	0.45 ± 0.02	0.50 ± 0.01	
	RC: Compressional resilience [%]		43.6 ± 1.4	41.6 ± 1.2	34.7 ± 0.6	
	TO: Thickness under 0.5 gf/cm² load [mm]		1.22 ± 0.04	1.26 ± 0.03	1.31 ± 0.02	
Surface	MIU: Mean coefficient of friction [-]	wale	0.165 ± 0.003	0.155 ± 0.002	0.175 ± 0.002	KES-FB4 Contact force of MIU and MMD : 50 [gf] contact force of SMD : 10 [gf] Tension of specimen : 20 [gf/cm]
		course	0.195 ± 0.002	0.201 ± 0.002	0.197 ± 0.005	
	MMD: Mean deviation of friction [-]	wale	0.007 ± 0.001	0.012 ± 0.003	0.007 ± 0.000	
		course	0.013 ± 0.002	0.015 ± 0.003	0.011 ± 0.002	
	SMD: Geometrical roughness [micron]	wale	11.54 ± 0.3	13.5 ± 0.8	3.56 ± 0.3	
		course	11.87 ± 1.0	12.5 ± 0.7	7.7 ± 0.3	
Thermal transport	q-max [W/cm²]		0.101 ± 0.001	0.103 ± 0.001	0.103 ± 0.001	KES-F7 Thermo-Lab Sourc of heat : 30 [℃] ΔT : 10 [℃] Air verocity of Qd : 0.3 [m/s]
	Thermal conductance [W/(m²・K)]		61.1 ± 0.8	62.3 ± 0.7	63.4 ± 0.9	
	Insulation rate [%]		24.6 ± 0.8	23.9 ± 0.7	24.7 ± 0.4	
Moisture transport	Wicking ＆ Quick drying [%]		15.01 ± 2.2	14.4 ± 1.6	14.0 ± 1.7	BOKEN BQE A028
Air permeability	Air flow resistance [KPa・s/m]		0.044 ± 0.001	0.041 ± 0.001	0.084 ± 0.003	KES-F8 SENSE : H SPEED : 2 [cm/s]
	Weight [g/m²]		144 ± 3	143 ± 5	157 ± 2	Electronic balance

The measurements revealed that the fabric sample C had significantly greater weight, thickness, and air flow resistance than the other two samples, which indicates that this sample had poor air permeability. The sample PP/C had the largest values of surface properties, MIU (mean coefficient of friction) of course direction, MMD (mean deviation of friction) of both directions, and SMD (geometrical surface roughness) of both directions. Multiple comparisons using

Tukey's test revealed that the SMD values of PP/C were significantly higher than the other two samples. Thus, the PP/C sample appeared to have features of poor skin texture.

3.2.3 Wearing experiment

Undershirts samples were made using these fabrics. Figure 3.2 shows the design of the undershirt sample and the length of each part of each size. There were three sizes of undershirts: M, L, and LL. Each participant pre-selected the size that best fits out of the three sizes. Three samples (PP/R/C, PP/C, and C) of undershirts of the selected size were prepared for each participant.



Size	M	L	LL
a	710	740	780
b	445	470	530
c	170	170	200
d	460	470	490
e	450	485	520
f	140	150	150
g	110	110	125
h	240	260	280
i	170	180	190

Unit: [mm]

Figure 3.2. Information of the undershirt samples (pattern, size)

Ten healthy Japanese male college students participated in the experiment (age: 21.9 ± 1.2 years, height: 175.6 ± 6.1 cm, mass: 63.9 ± 5.2 kg, body mass index (BMI): 20.7 ± 1.6). As with the participants in Chapter 2, they were only male participants, and they asked to refrain from alcohol and caffeine intake before the experiment. Each participant followed the experimental procedure for one sample per day, taking 3 days in total to complete the experiment. The order of wearing the three material samples for each participant was randomly selected. The information on the sample when worn was not given to the participants except for the size. A new undershirt sample was used in each experiment to avoid changing material properties of the samples. The experiment was carried out at the same time of day in consideration of the circadian rhythm of humans, to avoid potential bias resulting from the effect of thermoregulation.

Participants first changed clothes, putting on a T-shirt (100% cotton) and trousers (cotton 54% and polyester 46%) to ensure the same initial status. Participants then entered a room with constant temperature and relative humidity levels of 24°C and 50%, and rested for 15 min to allow their bodies to adjust to the temperature. ECG electrodes, and temperature and humidity sensors (Hygrochron; KN Laboratories, Inc., Osaka, Japan) were then attached to participants' skin as shown in Figure 3.3. The ECG electrodes were attached to the upper sternum and apical part of the participants via the chest bipolar induction method, and amplified by an ECG100C amplifier (BIOPAC Systems, Inc., Goleta, California, USA). The temperature and humidity sensors were attached to seven parts of the body (the left side of the chest, the abdomen, the upper back, the lower back, the left upper arm, the left femur, and the left calf). In this experiment, the materials of the blended yarn were changed from the viewpoint of hydrophobicity and hydrophilicity of fibers in the three types of undershirt samples. The thermal indicators were selected on the assumption that the thermal indices of temperature and humidity would also change when wearers exercised and perspired.

Each participant wore an undershirt sample randomly selected from three different kinds of materials, and the ECG electrodes were connected to an amplifier via a lead wire.

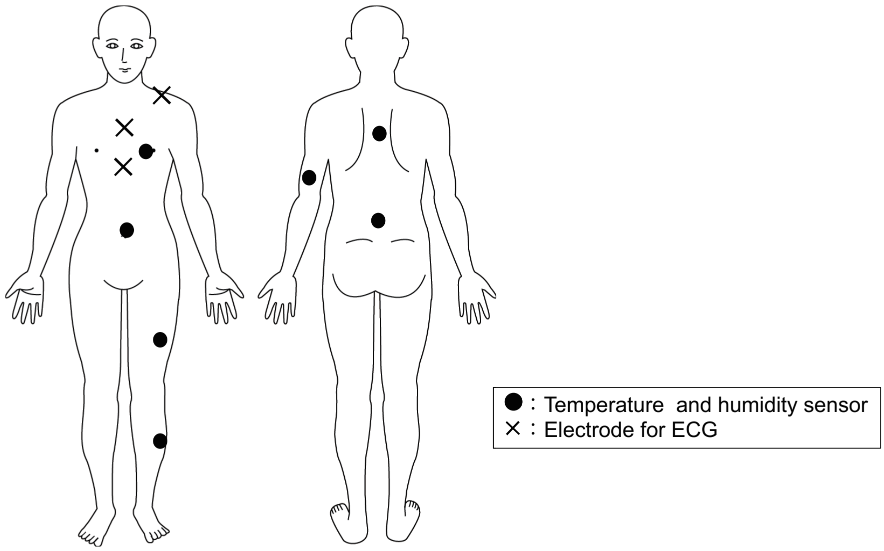


Figure 3.3. The position of the attached sensors–

The experiment took 60 min in total (Figure 3.4). This experimental protocol was the same as that of chapter 2. Each participant firstly rested for 20 min, then exercised on a treadmill (AFR2115; ALINCO, Inc., Osaka, Japan) for 10 min at an intensity of 55%–65% of their maximum heart rate, calculated using the expression “220 − age”. This exercise intensity is the same as that of chapter 2. After exercising, each participant rested again for 30 min.

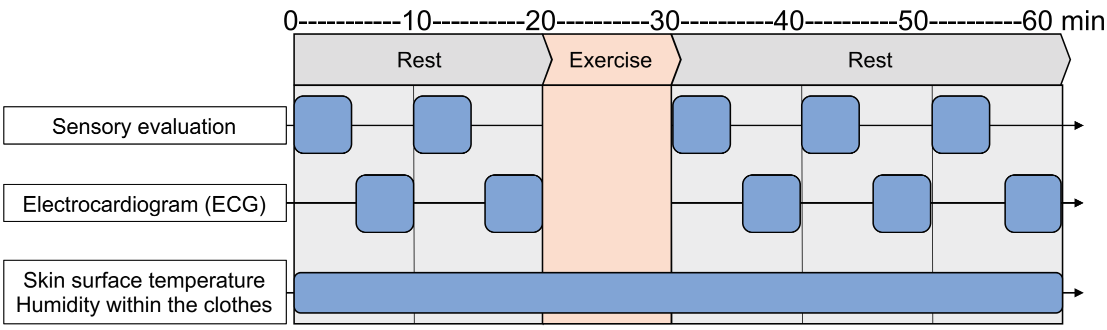


Figure 3.4. Experimental protocol of wearing experiment

In this 60-minute experiment, the psychophysiological responses of the participants were measured every 10 minutes except for 10 minutes during the exercise period from 20 to 30 minutes (refer to Figure 3.4). A total of five measurements were performed in a single experiment. As a measurement procedure, first, a sensory evaluation was performed to measure psychological responses. Furthermore, the physiological responses when worn were measured. After the sensory evaluation, ECG measurement was performed for 2 minutes. In addition, skin temperature and humidity within the clothes were constantly measured using a temperature and humidity sensor attached to the body to monitor the wearer's body status.

In psychological response measurement, the SD method was employed. Sensations of participants were measured five times in total at intervals of 10 min, except while exercising. "Neither", "Slightly", "Very" and "Extremely" were used as the adjectives, and the evaluation of the adjectives was scored by seven points (−3 to +3). There were 10 evaluation term pairs: Hot–Cool, Cold–Warm, Sticky–Slippery, Stuffy–Dry, Poor texture–Good texture, Rough–Smooth, Hard–Soft, Restrained–Unrestrained, Thick–Thin, and Uncomfortable–Comfortable (Table 3.4). The two pairs, Hot–Cool and Cold–Warm, were used for warmth sensation to confirm in detail the comfort of warmth. In these two pairs, hot and cold, which have negative meanings, were placed in the negative direction, and cool and warm, which have positive meanings, were added in the positive and comfortable direction.

Table 3.4. Evaluation term pairs of SD method

Evaluation term pairs
Hot–Cool
Cold–Warm
Sticky–Slippery
Stuffy–Dry
Poor texture–Good texture
Rough–Smooth
Hard–Soft
Restrained–Unrestrained
Thick–Thin
Uncomfortable–Comfortable

Temperature and humidity sensors were used to measure the mean skin temperature and the mean humidity within the clothes. The mean skin temperature (Tsk) was calculated according to Ramanathan's four-point method, as expressed by equation (3.1) [56].

$$T_{sk} = 0.3\,(T_{chest} + T_{arm}) + 0.2\,\left(T_{femur} + T_{calf}\right) \qquad (3.1)$$

where, T_{chest} = skin temperature of the left side of the chest [°C];

T_{arm} = skin temperature of the left upper arm [°C];

T_{femur} = skin temperature of the left femur [°C];

T_{calf} = skin temperature of the left calf [°C].

The mean humidity within the clothing was calculated from the results obtained by the sensor at four measuring points (the left side of the chest, the abdomen, the upper back, and the lower back). The average value of the four points was used as the representative value of the mean humidity within the clothing.

The ECG signal was sampled at a frequency of 2000 Hz. The results of the ECG—which measures autonomic nervous activity—were analyzed. LF/HF was calculated in the same way as in Chapter 2.

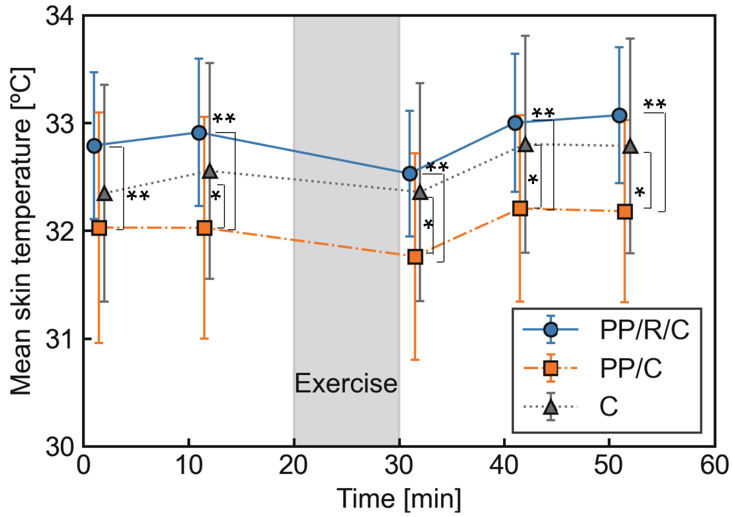
In the wearing experiment, a two-way analysis of variance (ANOVA) was performed to detect significant differences among two main effects (i.e., the sample and elapsed time) and interaction between them. There were three levels of sample (i.e., PP/R/C, PP/C, and C) and five levels of elapsed time (i.e., 1-10, 11-20, 31-40, 41-50, 51-60min). Additionally, Tukey’s test was used for multiple comparisons.

3.3 Results

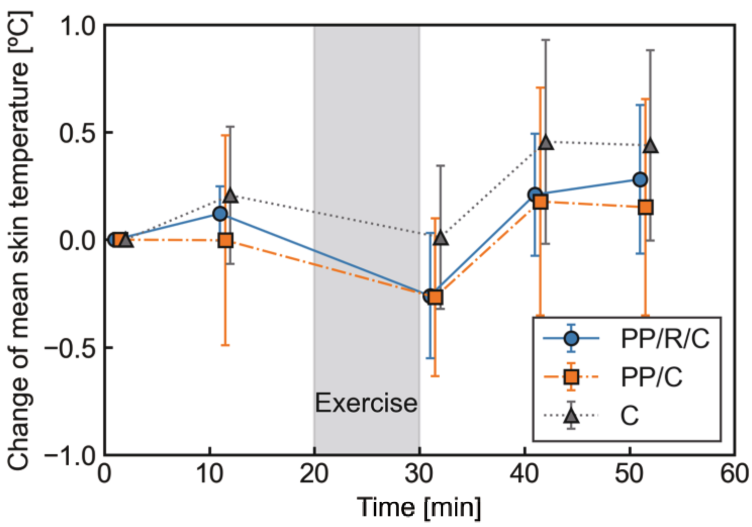
3.3.1 Physical conditions of the wearing state

The characteristics of the collected data are shown from here. First, the changes in thermal physical body indices when wearing each sample are shown. The mean skin temperature and the mean humidity within the clothing were calculated from the measurements of temperature and humidity sensors. The mean values and standard deviation of nine participants were calculated except for one participant who could not measure due to sensor malfunction in physiological measurement. Additionally in the PP/C condition, the mean value was calculated from the data of eight participants because of a sensor malfunction in another participant. The values at 1, 11, 31, 41, and 51 min corresponding to the beginning of each measurement phase were used as represented values.

Figure 3.5 shows the values of mean skin temperature. Figure 3.5 (a) is the absolute value of mean skin temperature, and Figure 3.5 (b) is the relative value from initial temperature to consider changes the state of after exercise. Multiple comparisons for absolute values revealed that there were significant differences between PP/R/C and PP/C at all time (** $p<0.01$, * $p<0.05$). Additionally, there were significant differences between C and PP/C at 10, 30, 40, 50 min.



(a) Absolute values



(b) Relative values

Figure 3.5. Mean skin temperatures (**$p < 0.01$, *$p < 0.05$)

The average skin temperature already differed depending on the sample at the start of the experimental period. This is because it took a few minutes to attach the measurement sensors. Time had therefore passed since the sample clothes were first put on and there were thus differences in thermal transport characteristics of each sample at the start of the experiment. The overall temperature trend was PP/R/C > C > PP/C. This trend was related to the insulation rate of the material property. The skin temperature of PP/C was lowest because PP/C had high air permeability and the lowest heat insulation rate among samples.

In the Figure 3.5 (b), after exercise (20 to 30 minutes), the mean skin temperature increased for all samples. This phenomenon was caused by stopping exercise, the flow of the body surface air layer was stopped and fluttering of clothes was eliminated, and due to a delay in heat generation caused by exercise. The increase in skin temperature was highest for C among the samples.

Figure 3.6 shows the values of mean humidity within the clothing. Multiple comparisons revealed that there were significant differences between the samples in the 31 min after exercise (**p<0.01, *p<0.05). The humidity within C increased rapidly and the value was significantly higher than in the other samples after exercise.

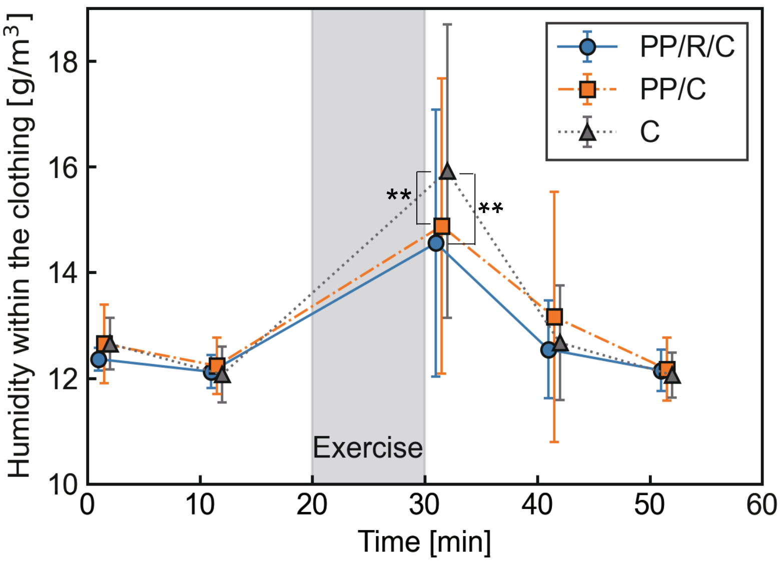


Figure 3.6. Mean humidity within the clothing (**$p < 0.01$, *$p < 0.05$)

3.3.2 Change in psychological sensations between samples and between processes

The average values and standard deviations of the data obtained for each evaluation term pair in the SD method were calculated for each of the ten participants. The scores for each evaluation term pair of each sample are shown as below.

Figure 3.7 shows the scores for the sensory evaluation Uncomfortable–Comfortable. The scores decreased immediately after exercise, and the samples tended to be rated as uncomfortable. Multiple comparisons using Tukey's test revealed a significant difference between the scores for PP/R/C and other samples at 30 and 40 min. In the PP/C condition, the decrease in comfort score was larger than in the other two samples. Subsequently, the scores increased, and comfort tended to recover.

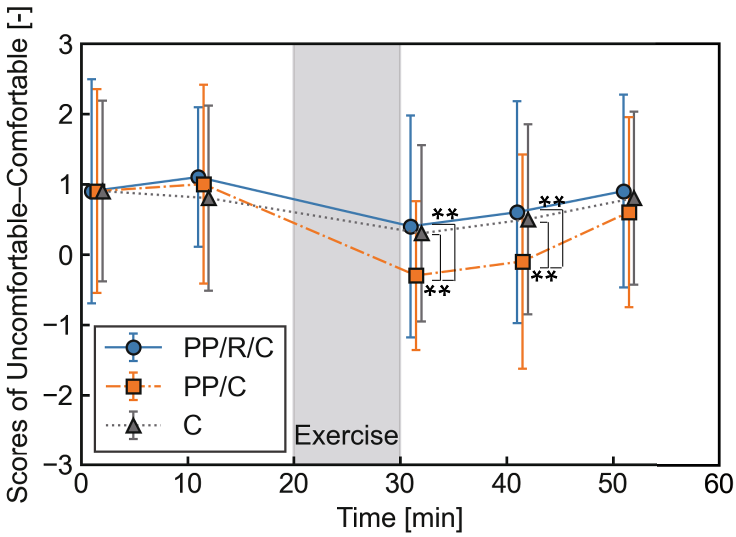


Figure 3.7. Uncomfortable–Comfortable sensory evaluation scores over time (**$p < 0.01$, *$p < 0.05$)

Figures 3.8 and 3.9 show the values of sensations of Hard–Soft and Rough–Smooth, respectively. In these evaluation terms, values in the PP/C condition tended to be relatively small. These results tended to be similar to the scores of Uncomfortable-Comfortable.

In terms of softness sensation, significant differences were observed in multiple comparisons at 0, 10, 40 and 50 min between PP/C and PP/R/C. The values for PP/C were significantly smaller than those for PP/R/C, which indicates that the PP/C sample fabric was rated by participants as feeling relatively hard.

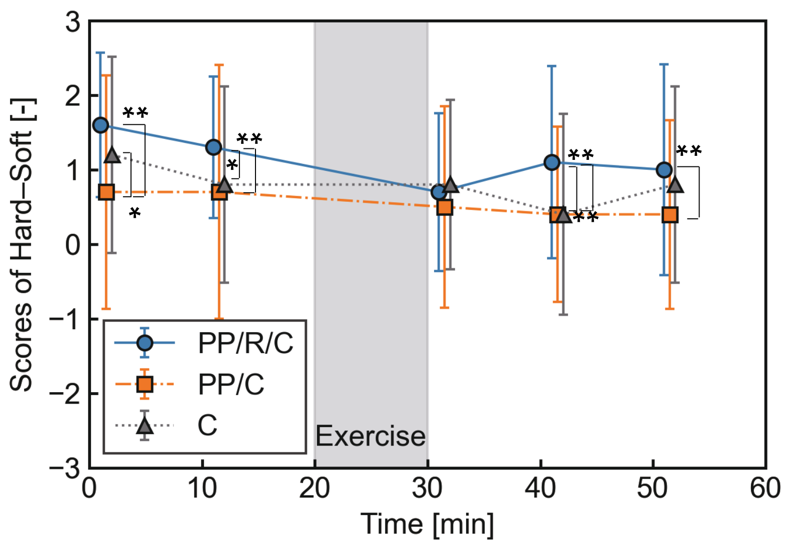


Figure 3.8. Hard–Soft sensory evaluation scores over time (**$p < 0.01$, *$p < 0.05$)

In terms of sensation of smoothness, significant differences were observed in multiple comparisons at the time of 0, 30, 40 and 50 min between PP/C and PP/R/C. The values for PP/C were significantly lower than that of PP/R/C, which indicates that participants felt the PP/C sample fabric was relatively rough fabric. Additionally, there were significant differences between PP/R/C and C at the time of 30 and 40 min (after exercise). The values for C were significantly lower than PP/R/C, which indicates that sensation of smoothness of C became worse than PP/R/C fabric.

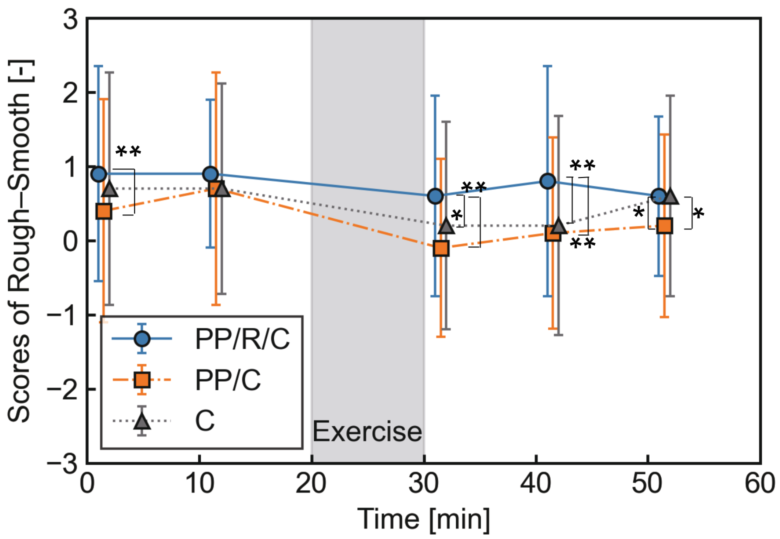


Figure 3.9. Rough–Smooth sensory evaluation scores over time (**$p < 0.01$, *$p < 0.05$)

As sensations related to thermal comfort, Figure 3.10 and 3.11 show the scores for the sensory evaluation Hot-Cool and Stuffy–Dry, respectively.

Figure 3.10 shows the scores of the sensory evaluation Hot-Cool. Analysis through multiple comparisons revealed significant differences at the time of 0, 10 and 50 min between PP/R/C and other two samples. PP/R/C had significantly lower score than the other two samples at the time immediately after putting on the undershirt sample. The result has the same trend as absolute value of the mean skin temperature (Figure 3.5).

Figure 3.11 shows the scores of the sensory evaluation Stuffy-Dry. Multiple comparisons using Tukey's test revealed a significant difference between the scores for the PP/C and C samples at 40 min. The value for C was higher than the value for the PP/C samples immediately after exercise. Regarding the PP/R/C and PP/C samples, although the scores decreased after exercise (at 30 min), the values increased 10 min later (at 40 min). In contrast, the Stuffy sensation took longer to return for the C sample than for the two PP samples.

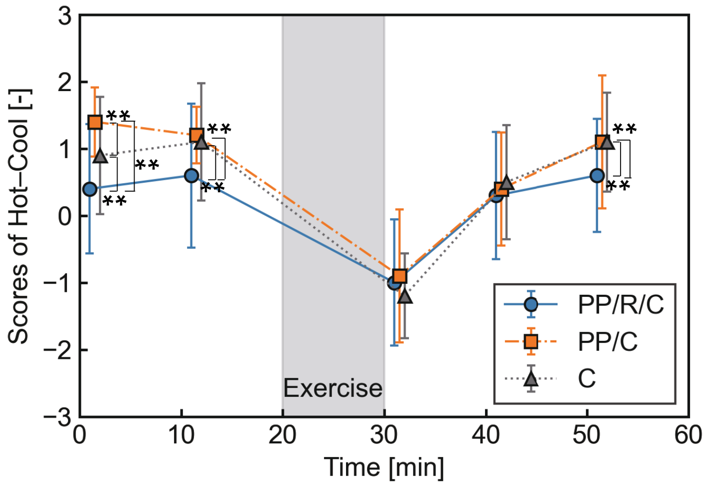


Figure 3.10. Hot–Cool sensory evaluation scores over time (**$p < 0.01$, *$p < 0.05$)

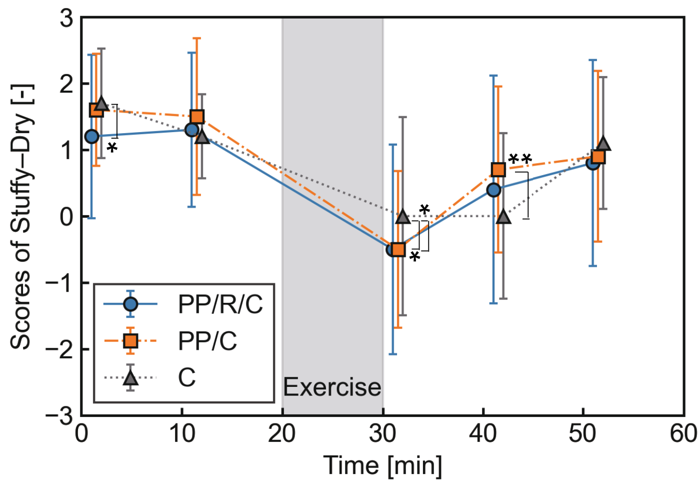


Figure 3.11. Stuffy–Dry sensory evaluation scores over time (**$p < 0.01$, *$p < 0.05$)

3.3.3 Change in physiological responses

As one of the indicators of autonomic nervous activity, the value of LF/HF, which was thought to be highly related to clothing comfort sensation in Chapter 2, was used. Figure 3.12 shows the average LF/HF scores for the nine participants. The value for C increased after exercise. The multiple comparisons revealed significantly higher values for C than for the other two PP blended samples at 40 min.

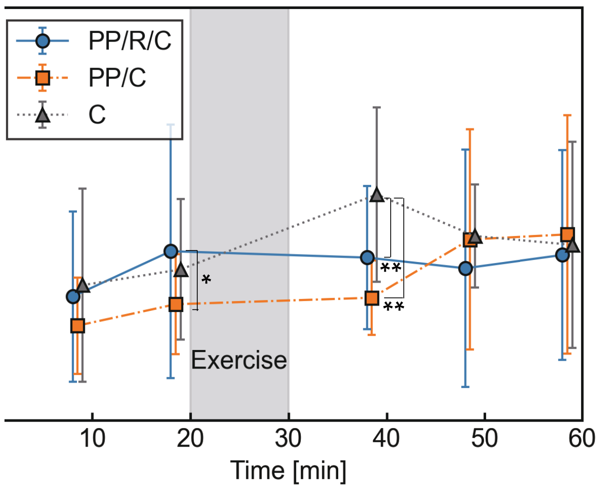


Figure 3.12. Low frequency/high frequency (LF/HF) over time (** $p < 0.01$, * $p < 0.05$)

3.3.4 Analysis of psychological structures of clothing comfort sensation of each sample

Multiple regression analysis was performed for each sample to investigate the psychological structures of clothing comfort sensation of three samples made from different blended yarns. The objective variable was score of Uncomfortable-Comfortable for the whole time of each sample, and the explanatory variables were other evaluation term pairs. The Excel statistics tool ver.2017 (Social Information Service Co., Ltd.) was used for analysis, and forward selection method was used at this time.

Table 3.5. Results of multiple regression analysis for each sample

Objective variable	Explanatory variable	Partial regression coefficient	Standard error	Standardized partial regression coefficient	*F* value	*t* value	*p* value	
Uncomfortable–Comfortable of PP/R/C (Adjusted R^2 = 0.67)	Stuffy-Dry	0.36	0.13	0.39	7.95	2.82	0.01	**
	Poor texture-Good texture	0.33	0.15	0.32	5.01	2.24	0.03	*
	Hard-Soft	0.24	0.14	0.20	2.81	1.68	0.10	
	Constant term	0.01	0.17	-	0.00	0.05	0.96	
Uncomfortable–Comfortable of PP/C (Adjusted R^2 = 0.78)	Poor texture-Good texture	0.71	0.08	0.66	72.03	8.49	0.00	**
	Sticky–Slippery	0.50	0.11	0.44	21.71	4.66	0.00	**
	Cold-Warm	0.20	0.11	0.15	3.35	1.83	0.07	
	Constant term	-0.23	0.11	-	4.33	-2.08	0.04	*
Uncomfortable–Comfortable of C (Adjusted R^2 = 0.82)	Poor texture-Good texture	0.53	0.11	0.54	23.23	4.82	0.00	**
	Hard-Soft	0.35	0.10	0.35	12.19	3.49	0.00	**
	Stuffy-Dry	0.11	0.08	0.11	2.29	1.51	0.14	
	Constant term	-0.03	0.10	-	0.07	-0.26	0.79	

**: p<0.01, *: p<0.05

Table 3.5 shows the results obtained from multiple regression analysis performed on each sample. For all samples, Poor texture-Good texture was significantly used as an explanatory variable, and the standard regression coefficient of the term was high.

Considering each sample, Stuffy-Dry was selected for PP/R/C, and Sticky-Slippery were selected for PP/C as significant variables. Since the standard partial regression coefficients of these variables were high, they had a high effect on the objective variable: the clothing comfort sensation. When wearing PP samples, sensations of stuffiness and stickiness, which are affected by sweating, were the factors that greatly affected clothing comfort sensation.

For the sample C, Hard-Soft was a significant explanatory variable in addition to Poor texture-Good texture. Therefore, for Sample C (with 100% cotton), the impression of compression softness, and good skin touch had a big influence on the clothing comfort sensation.

In this way, the clothing comfort sensation was basically affected by the skin texture sensation. In addition, the impression with a high degree of influence changed depending on the differences in characteristics of each sample.

3.4 Discussion

3.4.1 Relationships between psychophysiological responses and material properties

In the results of the wearing experiment, the values of psychophysiological responses differed depending on the sample. In sample C, the value of humidity within the clothes was significantly higher than that for the other samples after exercise (Figure 3.6). This result was greatly influenced by the air permeability of the samples. It is presumed that the heat and humidity in the sample C increased significantly due to exercise because of low air permeability and low moisture transport property. The sample C was a thicker and its air permeability was significantly lower than the other two samples. Similarly, because of the influence of air permeability, the value of C was significantly higher for the psychological sensation of stuffiness at 40 min (10 min after the end of exercise). These results suggested that the humidity inside the clothes increased after exercise because of the low air permeability, and the change in humidity resulted in a high sensation of stuffiness after exercise. The analysis of the LF/HF scores revealed significantly higher values for sample C than for the two other samples after exercise (Figure 3.12). The results suggested that the value of LF/HF, which is an index of the sympathetic nervous system, increased because the wearer felt thermal discomfort after exercise caused by a sensation of stuffiness.

In sample PP/C, the values of Uncomfortable–Comfortable tended to be smaller compared with the other samples after exercise. At 40 min, there was a significant difference between PP/C and PP/R/C. Similarly, the values of the sensation of hardness and smoothness of the fabric at the time of contact were smaller than those of PP/R/C. In terms of material property values, PP/C had significantly large values for surface roughness, which suggests that the wearer may have perceived this surface property when wearing the fabric. PP/C had a relatively low sensation of comfort associated with the skin contact after exercise, and the LF/HF value of the sympathetic nervous system also gradually increased from the start of the experiment. There was a significant difference before and after exercise. Because the discomfort sensation was caused by negative skin contact sensations, the LF/HF value was expected to also increase.

3.4.2 Psychological structures of clothing comfort sensations in each sample

Multiple regression analysis with comfort as the objective variable was performed for each sample. As a result, the skin contact sensation was commonly selected as the explanatory variable, and another term different depending on the sample was selected as a significant variable in each sample.

Considering each sample, Stuffy-Dry was selected for PP/R/C, and Sticky-Slippery were selected for PP/C significantly. It seems that the sensation related thermal, moisture and air permeability greatly affected clothing comfort sensation in samples using PP blended yarn. This also corresponded to the values of the material properties, and the PP blended yarn samples had remarkably better air permeability as compared with C. In addition, the transpiration of moisture was also PP/R/C > PP/C > C. For this reason, the PP blended yarn samples, which had the better air permeability and the moisture transport characteristics, evoked the low stuffy sensation, and greatly affected the clothing comfort sensation.

For the sample C, Hard-Soft was a significant explanatory variable in addition to Poor texture-Good texture. Since C made of 100% cotton was the thickest and had the highest WC and smallest SMD in material properties. So, the sample had compressional softness and low roughness. It is thought that the good mechanical contact sensation had a great influence on the clothing comfort sensation.

3.5 Summary

In the current chapter, three types of undershirts were produced from PP blended yarns or cotton spun yarn, and the various material properties of fabric samples were measured to collect a range of psychophysiological data for ANN analysis. Using these three fabric samples, wearing experiments were conducted and psychophysiological responses were measured to analyze the structure of clothing comfort sensation.

The results of the wearing experiments revealed that differences in reactions to psychophysiological responses were caused by differences in the material properties of the undershirt samples. Figure 3.13 shows the summary of the results in this chapter. It was found that the humidity within the clothing after exercise rapidly increased in sample C(100% cotton sample), which had low air permeability. Consequently, it took longer for the sensation of stuffiness to decrease. In addition, the wearer experienced sensations of hardness and roughness when wearing sample PP/C, which had a high level of surface roughness and a relatively large coefficient of friction. Because of the influence of these negative skin contact sensations, the clothing comfort sensation after exercise in the PP/C condition was lower than that for the other two samples.

Multiple regression analysis was used to analyze the psychological structure of clothing comfort sensation for each sample. The results revealed that the selected explanatory variables corresponded to the features of the material properties of each sample. For the PP blended samples, which have better moisture transport and air permeability properties, the sensation related to the thermal comfort properties affected the clothing comfort sensation. In addition, the sensation of softness had a strong influence on sample C (100% cotton sample), which had high thickness and soft compression properties. Therefore, the psychological structures of clothing comfort sensation varied depending on the material characteristics of each sample. Using the data corresponding to these characteristics, the clothing comfort sensation was evaluated using an ANN in the next chapter.

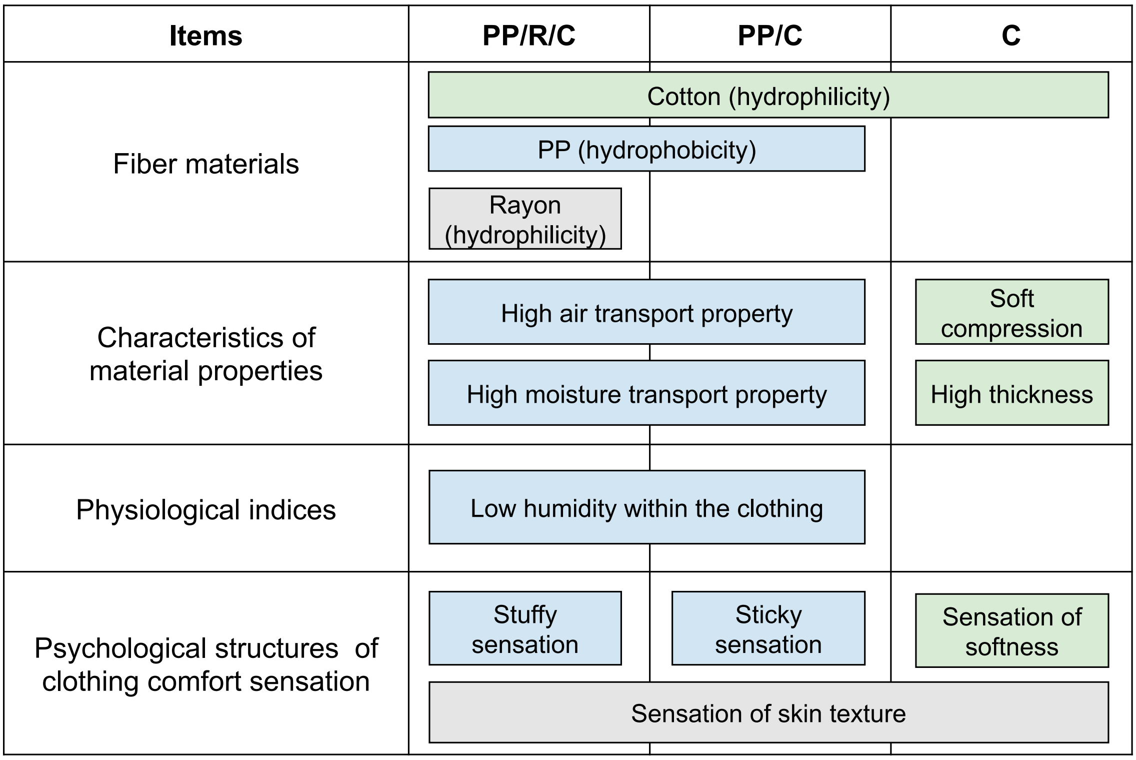


Figure 3.13. Summary of the results in Chapter 3

Chapter 4. Evaluation of clothing comfort sensation using artificial neural networks with psychophysiological responses as input data

4.1 Introduction

As reported in previous studies and revealed by the findings presented in Chapter 2, the measurement of human psychophysiological responses and linear analysis were effective methods for evaluating clothing comfort sensation. However, although some results showed linear relationships, previous studies have not confirmed that human physiological and psychological responses are always highly linear. For example, the relationship between the psychological sensation of stuffiness and CVRR, which is a physiological index, were not found to be simple linear relationships in Chapter 2. Non-linear relationships were also reported in previous studies [25, 26]. Therefore, it may be more suitable to use ANN analysis than conventional linear analysis methods, because ANNs are more similar to the human brain structure and have flexible computing ability. No previous studies have combined ANN and psychophysiological response measurement for evaluating clothing comfort sensation. Therefore, in this chapter, evaluation of clothing comfort sensation was conducted using ANN analysis in combination with the psychophysiological response data obtained in Chapter 3.

The relationships between input three conditions were investigated: (1) physiological responses only; (2) psychological responses only; and (3) both psychological and physiological response data. Furthermore, the prediction accuracy by conventional linear analysis using multiple regression analysis was compared with the accuracy of ANN. The purpose of this chapter was to verify the effectiveness of the clothing comfort sensation evaluation method using ANN. The findings of this study provide a first step toward constructing a more accurate ANN model, providing a tool for increasing understanding of clothing comfort sensation, and informing the development of useful tools for creating comfortable undershirt products.

4.2 Methods for evaluation of clothing comfort sensation by the ANN

4.2.1 Data collection

The data of the wearing experiment in Chapter 3 was used for the training data and constructing model by ANN. In the experiment, the state of the human condition changed variously in an environment where sweating occurs, and the three types of undershirt samples were used from a blended yarn in which the material ratio was changed. So, there were various clothing comfort sensations with various human conditions changed from the obtained physiological and psychological responses.

As the psychological response data, I used the semantic differential (SD) method. There were 10 evaluation term pairs: Hot–Cool, Cold–Warm, Sticky–Slippery, Stuffy–Dry, Poor texture–Good texture, Rough–Smooth, Hard–Soft, Restrained–Unrestrained, Thick–Thin, and Uncomfortable–Comfortable.

As the physiological responses, the thermal physiological indices calculated from the temperature and humidity sensor attached to the skin and the autonomic nervous system activity indices calculated from the ECG were used. Table 4.1 shows various indices calculated from the indices. Regarding the autonomic nervous system activity from ECG, various indices were calculated from the time domain and frequency domain of heart rate variabilities.

Ten participants were measured in the experiment. However, the data for one participant could not be used due to a failure during measurement in the physiological responses, so the data for nine participants was used in this experiment. The result of the study was from only data for nine Japanese male college students as a first step, and had limitations. It is necessary to continue to collect data on wearing for a wide range of ages, women, and nationalities to build a model that predicts the clothing comfort sensation from a versatile physiological and psychological responses in the future plan.

Table 4.1. Physiological indices calculated from the thermal physiological indices and the time domain and frequency domain of heart rate variability–

Physiological indices		Definition
Thermal physiological indices	Upper skin surface temperature [ºC]	Mean skin surface temperature of the upper 4 points (left chest, stomach, upper back, lower back)
	Mean skin temperature [ºC]	Mean skin temperature calculated according to Ramanathan's four-point method
	Humidity within clothes [g/m^3]	Mean humidity within clothes of the upper 4 points (left chest, stomach, upper back, lower back)
Time domain heart rate variability indices	HR [n/min]	Average total heart rate per 1 minute
	Mean NN [ms]	Mean of R-R intervals
	SDNN [ms]	Standard deviation of R-R intervals
	RMSSD [ms]	Square root of the mean of the sum of difference of successive R-R intervals
	NN count [n]	Total number of consecutive adjacent RR intervals
	SDSD [ms]	Standard deviation of difference between adjacent R-R intervals
	NN50 count [n]	Total number of consecutive adjacent RR intervals that differ by more than 50 ms
	pNN50 [%]	Percentage of number of R-R pairs that differ by 50 ms in the entire recording
	CVRR [%]	Coefficient of variation of R-R interval
Frequency domain heart rate variability indices	TF [ms^2]	Total spectral power (0-0.4Hz)
	VLF [ms^2]	Power in very low range frequencies (0.003-0.04Hz)
	LF [ms^2]	Power in low range frequencies (0.04-0.15Hz)
	LF amp [ms]	Mean amplitude of LF (square root of 2 times LF)
	LF norm [%]	Ratio of absolute value of LF and difference of TF and VLF
	LF ccv [%]	Coefficient of component variance of LF
	HF [ms^2]	Power in low range frequencies (0.15-0.4Hz)
	HF amp [ms]	Mean amplitude of HF (square root of 2 times HF)
	HF norm [%]	Ratio of absolute value of HF and difference of TF and VLF
	HF ccv [%]	Coefficient of component variance of HF
	LF/HF [-]	Ratio between LF and HF power
	HF/(LF+HF) [-]	Balance of HF in total of LF and HF

4.2.2 Data preprocessing

The psychological and physiological data obtained in the wearing experiment were preprocessed for use in the ANN. A total of 135 data points were obtained by measuring five times (0, 10, 30, 40 and 50 min) in one experiment of three samples (PP/R/C, PP/C, C) of nine participants each. Figure 4.1 shows the frequency distribution of Uncomfortable–Comfortable scores used for output. This frequency distribution shows the results of all data for all time zones. On a scale of −3 to +3, there were no data points for scores of −3 and only two data points for scores of −2. The two −2 data points were excluded because it was impossible to use such small amounts of data for ANN's training. Thus, five types of comfort states ranging from −1 to +3 were used in this chapter. In addition, because data could not be obtained for one participant in one experiment because of a malfunction of the temperature and humidity sensors, this participants' data in one experiment (five data points) were removed. Therefore, a total of 128 data points was used for this analysis.

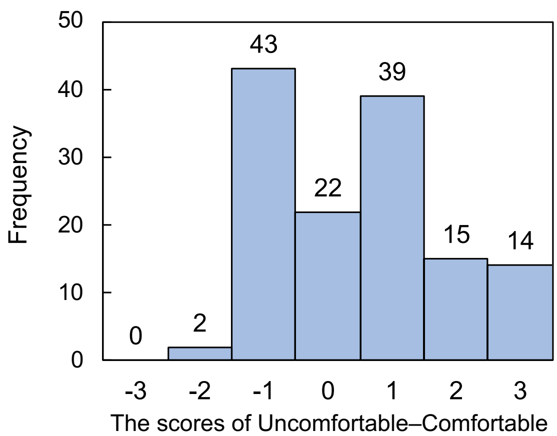


Figure 4.1. Frequency distribution of Uncomfortable–Comfortable scores of all data for all time zones

Each feature was individually normalized using Equation (4.1), and the feature quantity range was converted to a value in the range of 0 to 1. In general, a standardized transformation, which is transformed to the values with a mean of 0 and a standard deviation of 1 with a small effect of outliers, is performed on physiological response data. In this study, however, there were no data with large outliers, so normalization, which transforms the features to 0-1, was performed to reduce the learning cost of the calculation.

$$X = (X_i - X_{min}) \, / \, (X_{max} - X_{min}) \qquad (4.1),$$

where: X = normalized data in each indice;
X_i = actual data in each indice;
X_{min} = the minimum value of actual data in each indice;
X_{max} = the maximum value of actual data in each indice.

The normalized data were randomly divided for training, validation, and testing data using the train_test_split function of the scikit-learn library of Python 3.6.5. All 128 data points were randomly divided into 86 data points for training (68%), 22 for validation (17%), and 20 for testing (15%). At this time, Uncomfortable–Comfortable was set in the argument stratify of the train_test_split function so that the output the scores of Uncomfortable–Comfortable were divided at the same rate in train, validation, and test data.

4.2.3 Neural network architecture

Figure 4.2 shows the constructed ANN model and the indices used for input and output layers. Python 3.6.5 was used to construct the ANN models. The feature quantity to be input is the information of the sample and the values of indices obtained by measuring psychophysiological responses.

For the input layer, three input conditions have been prepared: (1) physiological responses only; (2) psychological responses only; and (3) both psychological and physiological response data. In addition, sample data was added under all conditions. As for the sample data, there were no data on the material properties corresponding to each participant's condition (same time zone), so the name number (PP/R/C; [1,0,0], PP/C; [0,1,0]], C; [0,0,1]) was used. In future studies, using a larger number of samples or developing the technology to collect physical data of materials when worn, we plan to use the material property values of each sample as the input amount. As data of psychological sensations, nine evaluation terms excluding "Uncomfortable–Comfortable" were used from the SD method. The data of physiological responses used for input are shown in Table 4.1. There were 24 physiological indices in total.

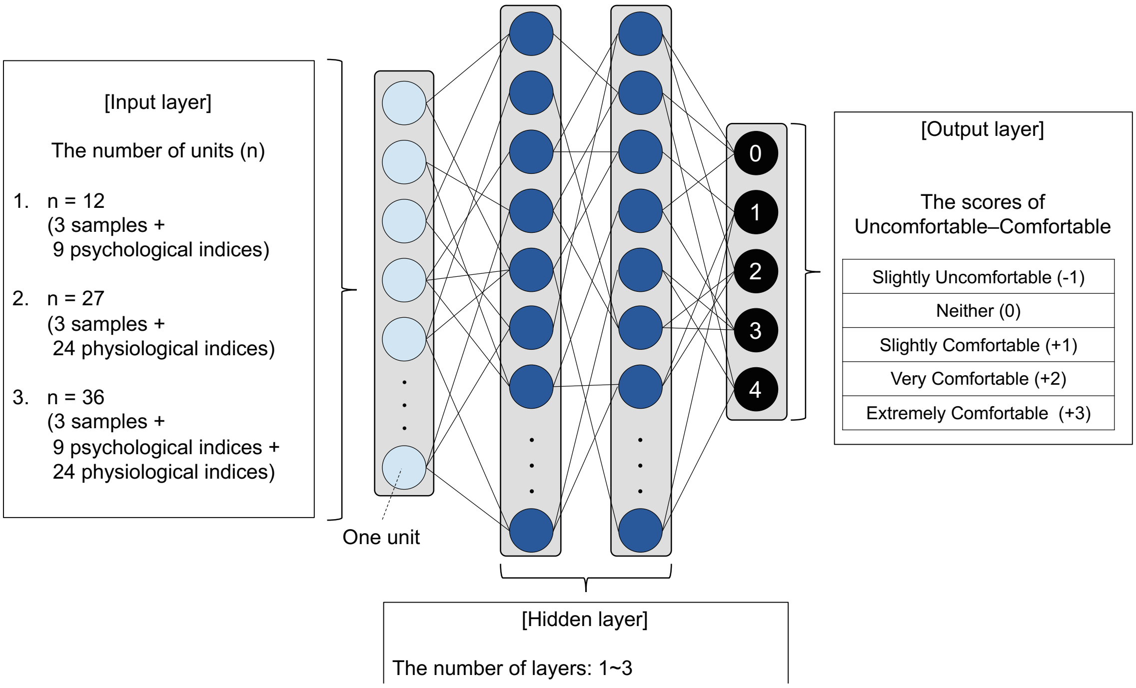


Figure 4.2. Artificial neural network architecture–

For the output layer, ratings of Uncomfortable–Comfortable of psychological responses were used. This value was originally used as an ordinal scale or an interval scale, but to make it a classification problem, these scores were also regarded as a nominal scale to classify the state of clothing comfort. Five types of clothing comfort states from −1 to +3 were classified. Therefore, the number of units in the output layer was five.

For the hidden layer, the number of layers ranged from 1 to 3. Using a large number of layers for deep learning is considered to be unsuitable when the numbers of data points are relatively small, as was the case here (only 128 data points). Therefore, the maximum number of hidden layers was three. The number of units in the hidden layer changes depending on the ratio of the number of input features (n) of input conditions. Therefore, the number of units in the hidden layer were n, 2n, or 3n. Additionally In other hidden layer conditions, the number was fixed and changed by a fixed amount (unit numbers were 30, 60, or 90). In summary, the total number of models verified this study were 18 by changing the number of units of hidden layers and the number of hidden layers. Table 4.2 shows all types of models with different structures.

Table 4.2. Unit numbers of hidden layers and the numbers of hidden layers of each neural network model

Model name	Number of hidden layer	Number of units of each hidden layer
n	1	n
2n	1	2n
3n	1	3n
n_n	2	First layer: n, Second layer: n
2n_2n	2	First layer: 2n, Second layer: 2n
2n_n	2	First layer: 2n, Second layer: n
3n_3n	2	First layer: 3n, Second layer: 3n
3n_n	2	First layer: 3n, Second layer: n
3n_2n_n	3	First layer: 3n, Second layer: 2n, Third layer: n
30	1	30
60	1	60
90	1	90
30_30	2	First layer: 30, Second layer: 30
60_60	2	First layer: 60, Second layer: 60
60_30	2	First layer: 60, Second layer: 30
90_90	2	First layer: 90, Second layer: 90
90_30	2	First layer: 90, Second layer: 30
90_60_30	3	First layer: 90, Second layer: 60, Third layer: 30

In all models, dropout was applied to output the feature quantity from the hidden layer to the next hidden layer or output layer to prevent overfitting. Dropout is a technique for addressing the overfitting. The idea is to randomly drop units along with their connections from the ANN during training [57]. This prevents units from co-adapting too much. The dropout rate was set to 0.2, it meant 20% of data were dropped from the hidden layer to the next hidden layer or output layer.

Rectified Linear Unit (ReLU) function [58] was used as the activation function in each interlayer. Because there were five states of clothing comfort classification problems, the softmax function was used as the activation function in the final output layer. The output label (the scores of Uncomfortable–Comfortable) were categorical encoded (one-hot encoding), and categorical cross entropy was used as the loss function.

4.2.4 Model training and evaluation

Training data were input to the above models to learn the features. The learning batch size was set to 20, and the epoch number was set to 300. Model learning was terminated when the loss of verification data did not decrease during the learning process. Adaptive moment estimation (Adam) [59] was used as the optimizing algorithm. Adam is one of the most sophisticated optimizing algorithms for ANN parameters. This algorithm was used because Adam can change the learning step by weight, with the previous gradient being most strongly related to the current gradient, and the uncertainty of the gradient update direction based on the annealing method. After the model was trained, unknown test data were used to predict the scores of Uncomfortable–Comfortable. The accuracy rate of the model was confirmed based on the actual scores of clothing comfort sensation of the test data and the predicted clothing comfort sensation.

4.3 Results

4.3.1 Accuracy of train and validation data after training process

Figures 4.3 and 4.4 show the box plot of percentage accuracy rate in train data and validation data by inputting and learning data under three conditions: (1) physiological responses only; (2) psychological responses only; and (3) both psychological and physiological response data in each model. A series of processes for constructing a model, training the model, and evaluating test data was performed five times. The maximum and minimum values and median accuracy rate values for five analyses in each model were shown in the box plot figures.

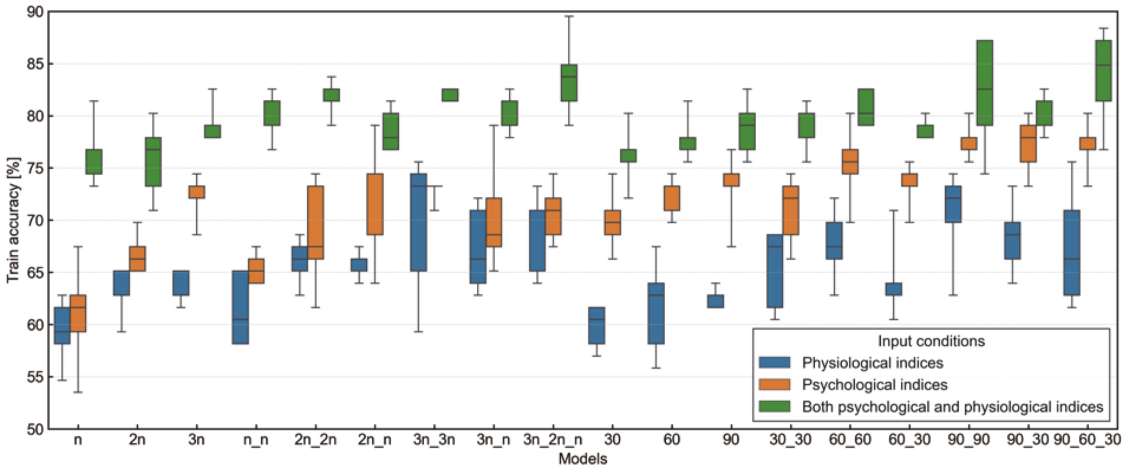


Figure 4.3. Accuracy of train data after training in each model

The results of the training data after training were completed tended to be highly accurate when both psychological and physiological indices were used in any models as shown in Figure 4.3. It was found that the accuracy of learning was improved by having both indices. Especially in model 3n_2n_n, the maximum value was the highest (89.5%), and the tendency of the training data was learned deeply.

As with the same tendency of train data, the accuracy rate of the validation data during learning was up to 86.3% for the model 30 when using both psychological and physiological data. The order of range of accuracy rate of the five times in each model was the use of only the physiological data < the use of only the psychological data < both psychological and physiological data. It showed the same tendency as the train data.

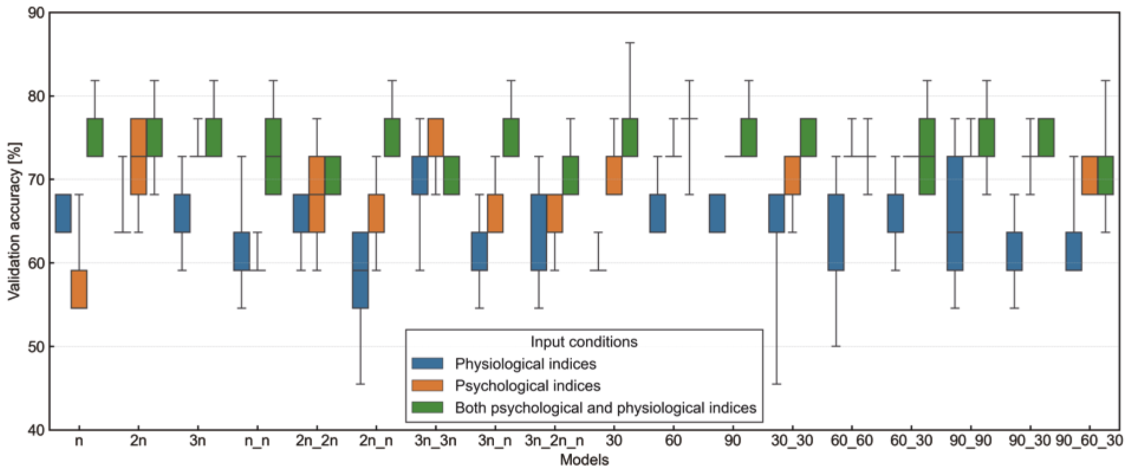


Figure 4.4. Accuracy of validation data after training in each model

4.3.2 Predicted accuracy of unknown test data

Figures 4.5 shows the box plot of percentage accuracy rate in unknown test data by inputting and learning only psychological data, only physiological data, and both psychological and physiological data in each model. The box plot was from the values of five times. Additionally, Table 4.3 shows the mean values of five-time analysis and the highest (maximum) values of the five times in each model.

In all models, accuracy was higher when both psychological and physiological data were combined than when psychological data and physiological response indices were used alone. Among the models using both psychological and physiological data, model 60_60 showed the highest accuracy (average accuracy 84%, maximum accuracy 85%). Comparing accuracy between the use of only the psychological data and only the physiological data revealed that accuracy was higher when only the psychological data was used. With this test data, we were able to predict the classification of clothing comfort sensation with an accuracy of up to 85% using both the wearer's subjective psychological data and objective physiological indices.

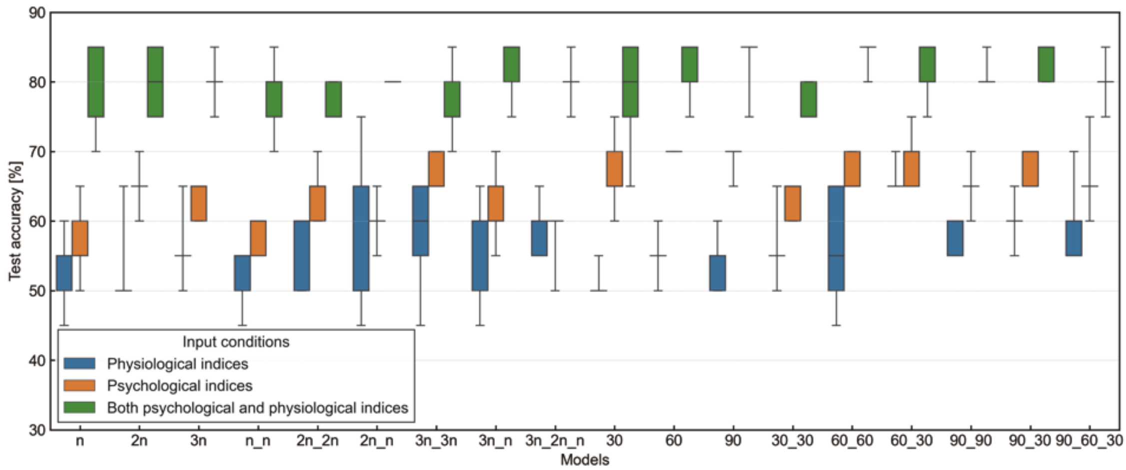


Figure 4.5. Accuracy of unknown test data in each model

Table 4.3. Mean and maximum values of accuracy of test data in each model

Model	Input condition					
	(1) Physiological indices		(2) Psychological indices		(3) Both psychological and physiological indices	
	Mean [%]	Max [%]	Mean [%]	Max [%]	Mean [%]	Max [%]
n	53	60	57	65	78	85
2n	53	65	65	70	80	85
3n	56	65	63	65	80	85
n_n	52	55	58	60	78	85
2n_2n	56	60	64	70	77	80
2n_n	57	75	60	65	80	80
3n_3n	58	65	67	70	77	85
3n_n	56	65	62	70	82	85
3n_2n_n	59	65	58	60	80	85
30	51	55	67	75	78	85
60	55	60	70	70	81	85
90	54	60	69	70	83	85
30_30	56	65	63	65	77	80
60_60	56	65	67	70	84	85
60_30	66	70	69	75	81	85
90_90	58	60	65	70	81	85
90_30	60	65	68	70	83	85
90_60_30	60	70	66	75	80	85

4.3.3 Analysis of misclassification

One example of classification of test data is shown when both psychological and physiological data were used in model 60_60, which had the highest accuracy rate of all models stably. Table 4.4 shows a confusion matrix between the actual values of the test data and the predicted values of the model after training. The best model accurately predicted the classification for 17 of the 20 tests data (= 85%) and three cases were misclassified. Of the three cases of incorrect predictions, there was one case in which the data indicated a "slightly uncomfortable state (−1)" but the case was classified as a "very comfortable (+2)", and two cases in which the data indicated "slightly comfortable state (+1)" but the case was classified as "slightly uncomfortable (−1)".

Table 4.4. Confusion matrix between the actual values of the test data and the predicted values of the best model 60_60

		Predicted value				
		-1	0	1	2	3
Actual value	Slightly Uncomfortable (-1)	6	0	0	1	0
	Neither (0)	0	3	0	0	0
	Slightly Comfortable (+1)	2	0	4	0	0
	Very Comfortable (+2)	0	0	0	2	0
	Extremely Comfortable (+3)	0	0	0	0	2

One of the above misclassification data was described in detail. Table 4.5 shows the psychological response values of the misclassified data that actual value was a slightly uncomfortable state (−1) and misclassified as very comfortable (+2). In this misclassified data, because sensations of softness and smoothness were high and the sensation of stuffiness was low, the ANN predicted that the clothing comfort sensation at this time was "very comfortable (+2)". However, in the actual judgement of wearer was a "slightly uncomfortable (−1)".

Table 4.5. Values of psychological responses and comfort prediction values of misclassified data

Evaluation term pairs	The values of a misclassification data
Hot–Cool	1
Cold–Warm	-1
Sticky–Slippery	2
Stuffy–Dry	2
Poor texture–Good texture	2
Rough–Smooth	2
Hard–Soft	2
Restrained–Unrestrained	2
Thick–Thin	3
Actual value of Uncomfortable–Comfortable	-1
Predicted value of Uncomfortable–Comfortable	2

Next, the difference in classification of test data between inputting conditions is described. In the best model 60_60, there were three data sets in which values were correctly predicted when the indices of both psychological and physiological data were input, but were incorrectly predicted when only the indices of the psychological data were input. Table 4.6 shows the three tests data and the probability distribution of each class used for prediction in each condition. In the probability density of Table 4.6, in the case of both psychological and physiological data, the correct value could be discriminated with a high probability of 0.4 or more. So, the predicted value and the actual value matched. However, in the case of only psychological responses, there was a high probability not only for the correct actual value but also for other wrong classes. The error value with the highest probability was wrongly selected for the predicted values.

Table 4.6. Test data that correctly predicted values when the indices of both psychological and physiological data were input but that were wrong when only the indices of the psychological data were input and the probability density of each class used for prediction

Test data	Actual value	Both psychological and physiological indices (n=36)						Psychological indices (n=12)					
		Predicted value	Probability distribution of class					Predicted value	Probability distribution of class				
			-1	0	1	2	3		-1	0	1	2	3
No. 1	0	0	0.12	0.47	0.29	0.06	0.06	-1	0.41	0.31	0.25	0.03	0.00
No. 2	2	2	0.00	0.11	0.26	0.44	0.19	1	0.01	0.15	0.45	0.24	0.16
No. 3	0	0	0.16	0.46	0.29	0.05	0.03	-1	0.41	0.31	0.25	0.03	0.00

4.3.4 Comparison of accuracy with multiple regression analysis

The prediction accuracy of the test data by ANN was compared with the method using the conventional linear analysis. A multiple regression analysis was performed to construct model as a conventional linear analysis for prediction of the clothing comfort sensation. The Uncomfortable–Comfortable scores of train data were used as objective variables, and the other psychological evaluation terms and physiological indices of train data were adopted as explanatory variables. It was same dataset as the ANN training. The analysis adopted the forward selection method.

The result of multiple regression analysis was shown in Table 4.7. From the physiological indices, HR and VLF, which are indicators of the sympathetic nervous system, were selected as explanatory variables. Among the psychological indices, Stuffy–Dry, Poor texture–Good texture, Hard–Soft, and Restrained–Unrestrained were selected as explanatory variables.

Table 4.7. Results of multiple regression analysis for train data

Objective variable	Explanatory variables	Partial regression coefficient	Standard error	Standardized partial regression coefficient	*F* value	*t* value	*p* value	
Uncomfortable – Comfortable (Adjusted R^2 = 0.80)	HR	2.34	0.99	0.41	5.57	2.36	0.02	*
	VLF	1.68	1.07	0.27	2.46	1.57	0.12	
	Stuffy-Dry	1.04	0.32	0.21	10.57	3.25	0.00	**
	Poor texture-Good texture	2.26	0.47	0.42	22.95	4.79	0.00	**
	Hard-Soft	1.74	0.44	0.31	15.55	3.94	0.00	**
	Restrained–Unrestrained	0.62	0.29	0.13	4.76	2.18	0.03	*
	Constant term	-2.12	0.88	-	12.61	-3.55	0.00	**

**: p<0.01, *: p<0.05

Next, the predicted Uncomfortable–Comfortable values of unknown test data were calculated using the prediction model created by the multiple regression analysis. The test data was the same as the 20 used in ANN.

Figure 4.6 shows a scatter plot of the actual and predicted test data. In many test data, the predicted values were similar to the predicted values. However, three data were much different values. The result was same tendency as ANN's predictions in Table 4.4. On the other hand, In the case of this linear prediction model, the predicted value when the actual value was -1 tended to be different from the actual value. These deviations caused the low adjusted coefficient of determination ($r^2 = 0.54$) and high mean absolute error (MAE). MAE is the average value obtained by calculating the absolute value of the difference between the predicted value and the actual value for each data, and is used as an index of accuracy. The higher this value, the larger the error.

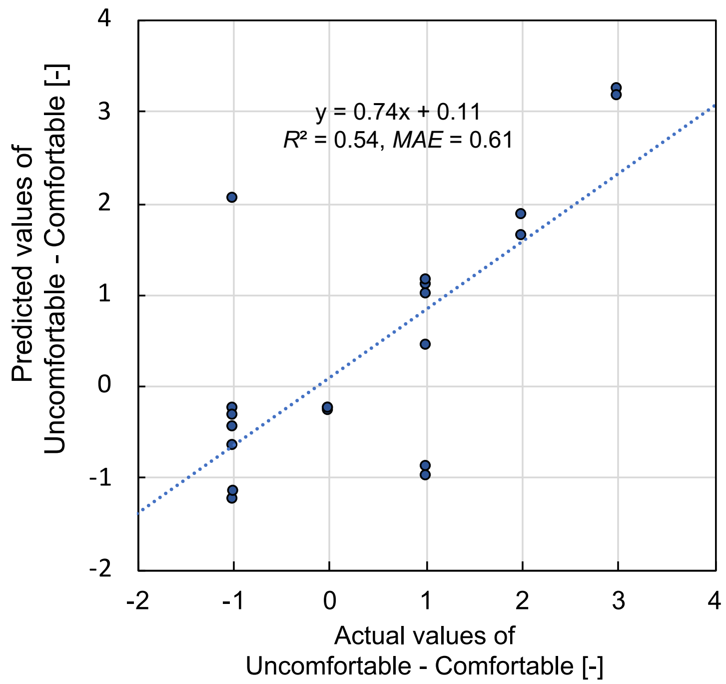


Figure 4.6. Scatter plot of actual scores and predicted scores of test data's Uncomfortable-Comfortable

Finally, the prediction results of the test data using the above multiple regression equation and the prediction results by ANN were compared. Figure 4.7 shows the actual values and predicter values of both multiple regression analysis and ANN methods. Regarding the result of multiple regression analysis, the predicted value in Figure 4.6 was rounded off and converted to an integer value in order to correspond with the result of ANN correctly. The darker the color of the marker of data, the larger the numbers of data at the coordinate point.

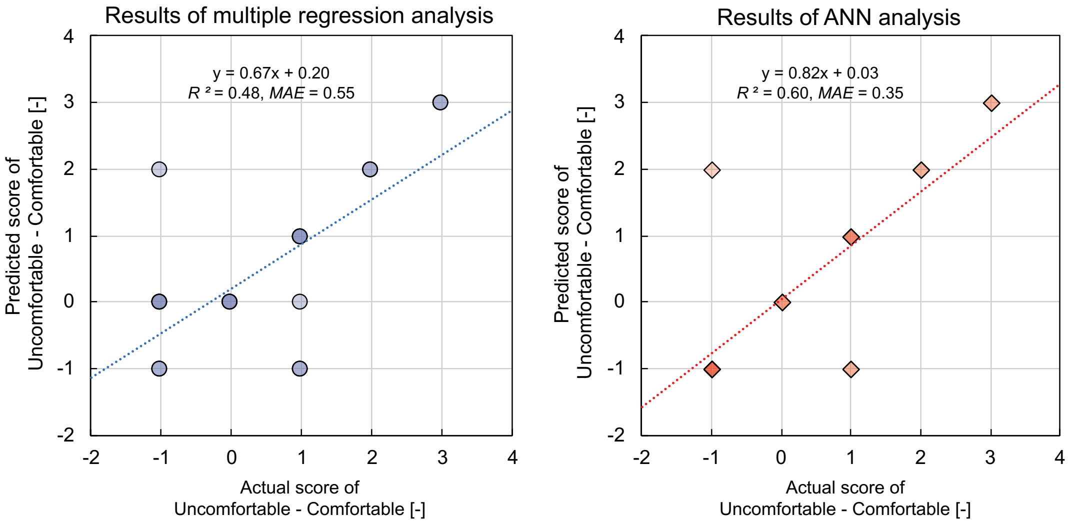


Figure 4.7. Comparison of test accuracy between multiple regression analysis and ANN analysis (transparency represented the number of data)

Comparing both figures, the results of multiple regression analysis showed more data points that differ from the actual values. In case of comparing the coefficient of determination (R^2), it was shown that ANN had a higher value and higher accuracy. Regarding MAE, the value of ANN analysis was smaller than that of multiple regression analysis. The error from the predicted value was smaller. These evaluation indices indicated the method of using ANN was better for prediction.

4.4 Discussion

4.4.1 Prediction results by the ANN

The attempt to predict the clothing comfort sensation from the data of various physiological and psychological indices revealed that it was possible to predict the clothing comfort sensation with a maximum accuracy of 85% using both physiological and psychological data as input parameters.

The architecture of the model that showed the highest accuracy with this input data contained two hidden layers, with 60 neurons in the hidden layers (Model 60_60). Because the number of learning data points was relatively small in this study, it was not suitable for deep learning using many hidden layers. The structure of this model, with two hidden layers and 60 units in each hidden layer, was suitable for the data set of this study. It is probable that the accuracy of the test data was stable without the risk of overfitting because the parameters were appropriate for the number of data points. With a greater amount of data, it may be possible for future studies to construct a model that performs deep learning and achieves a high accuracy rate.

The classification results of the test data after training of model 60_60 (the best model) were confirmed, and the data shown in Table 4.5 are provided as an example of misclassification. The example data were unusual, and these abnormal data may not have enabled learning with the relatively small amount of training data in the current study. Finally, the data were classified incorrectly. Misclassification could possibly be decreased in future studies with a greater amount of data and more variation.

In Table 4.6, the probability densities of each class in the output layer of the three data sets, which were correct when both the physiological and psychological data were used and could not be classified correctly only using psychological data, were confirmed. When only the psychological data were input, the probabilities were often dispersed. Consequently, the data were misclassified. This result appeared to indicate that a definitive evaluation cannot be made using psychological data alone. Therefore, the clothing comfort sensation could not be sufficiently predicted by the subjective psychological sensation alone, and it is useful to generate predictions by adding data for objective physiological responses to supplement unconscious physiological information.

Comparing the result of conventional multiple regression analysis with the prediction accuracy of unknown data, the ANN method was more accurate. The reason for this result was thought to be related to the explanatory variables of multiple regression analysis and the number of inputs amount of ANN. In the case of multiple regression analysis, it was necessary to select explanatory variables to prevent multicollinearity. Therefore, six indices with less linearity with each other were selected as explanatory variables using the stepwise method. However, these six explanatory variables often differed from the actual values, even if the values were rounded off when evaluating unknown test data. This was a value corresponding only to the existing training data, and lacked flexibility. In the case of ANN analysis, there were also disadvantages in using all variables as input amounts. One of disadvantages was that the scale of the network was increased, and it took more time to construct a model. In addition, it may be difficult to converge the error if all variables are used as input quantities when there is a high correlation between variables [60]. Despite these disadvantages, it was possible to calculate the relationships between all variables and ANN. Therefore, the ANN appeared to develop into a model that flexibly responded to unknown test data.

4.4.2 Importance of measuring both psychological and physiological responses

The input amount of ANN was tested under three conditions: (1) when only physiological response indices were used; (2) when only psychological response indices were used; and (3) when both physiological and psychological indices were used. The results revealed that the prediction of clothing comfort sensation was optimal when using data of both subjective psychological responses and objective physiological response indices. It was not possible to evaluate the clothing comfort sensation from one component of the response with high accuracy. In particular, the mean prediction accuracy was only 51%–66% when the analysis was based on physiological information alone. The results revealed that a high level of accuracy was achieved by inputting both psychological sensations and physiological responses of the wearing state because the amount of information increased by obtaining two aspects of the component of clothing comfort sensation.

As mentioned in Chapter 1, clothing comfort sensation is a complex structure composed of three main independent elements of psychological, physical, and physiological aspects between humans and the environment. Each element exerts its own influence. The current ANN results revealed the effectiveness of measuring both psychological and physiological responses for the evaluation and prediction of the complex clothing comfort sensation. As originally hypothesized, the estimated accuracy of clothing comfort sensation was improved by incorporating physiological data. Measuring both psychological sensations and physiological responses appeared to have a complementary effect, leading to a better expression of clothing comfort sensation. It is necessary to measure psychological sensations and physiological states of the body including the autonomic nervous system activity when considering the clothing comfort sensation, which is a complex structure. The results indicated that ANN provided a good analysis tool for handling human sensation and response data and performing flexible analysis, and it was possible to obtain a high level of accuracy using this approach.

4.5 Summary

In this chapter, the clothing comfort sensation of the wearer was predicted using ANN and psychological sensation and physiological response data, including ECG and thermo-physiological indices in Chapter 3. Figure 4.8 shows a summary of the results presented in this chapter.

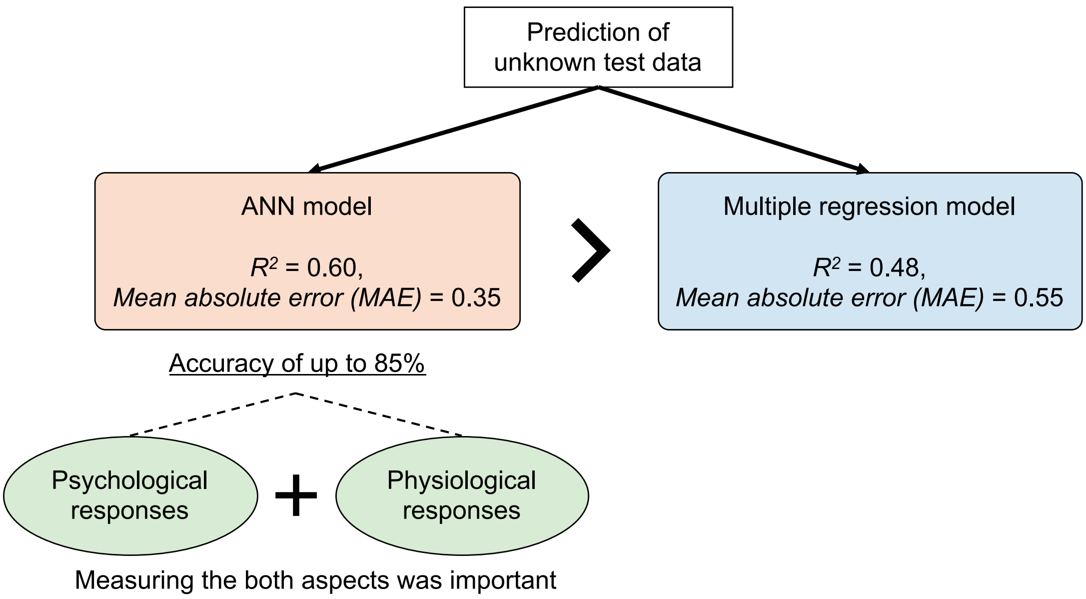


Figure 4.8. Summary of the results presented in Chapter 4

The results revealed that it was possible to predict the sensation with an accuracy of up to 85% when using both physiological response and psychological response data as input values. The results indicated that it was important to measure subjective psychological sensations and objective physiological responses, including thermophysical and autonomic nervous system activity data for evaluation and prediction of complex clothing comfort sensations. Furthermore, comparison of the prediction accuracy of unknown data with the results of conventional multiple regression analysis revealed that the coefficient of determination (R^2) of the ANN had a higher value and lower mean absolute error. It indicated that the ANN method was more accurate for the prediction of clothing comfort sensation. Therefore, the findings suggested that the method using ANN and measuring data of psychological sensations and physiological responses was effective for the evaluation of clothing comfort sensation.

In the present study, specific material property values were not used as input values because there were no material properties in the worn state and only three fabric samples were prepared. In future, measuring the material property values of many samples and clothes and combining them with input values will be useful for developing an ANN model with better performance accuracy.

Chapter 5. Conclusions

In this thesis, a method for evaluating clothing comfort sensation using ANN for non-linear analysis was verified. As a preliminary step, in Chapter 2, the effectiveness of psychophysiological response measurement using conventional linear analysis was confirmed with undershirt samples that had minute differences in material properties before ANN analysis. Two types of undershirt samples were constructed from PET and PP. These fibers had relatively similar properties with the same hydrophobic fibers when wearing undershirt samples with minute material properties. The evaluation scores of clothing comfort in the wearing experiments revealed a high negative correlation with LF/HF values, which is an index of sympathetic nervous system activity. The findings indicated that it was possible to evaluate the clothing comfort sensation from the sympathetic nervous activity index when wearing status changed significantly because of exercise or perspiration. However, a difference between samples was not detected in LF/HF values. Measures in which a minute sample difference could be confirmed were as follows. Wearers discriminated the differences between coolness and stuffiness sensations caused by the minute thermal and moisture transport characteristics of the undershirt samples. Furthermore, differences in the sensation of stuffiness were associated with CVRR, which is an index of autonomic nervous system activity. This finding indicated that the sensation of complex thermal discomfort can be evaluated using CVRR as an index of parasympathetic nervous system activity. Using this approach, even when undershirts with minute material differences were worn, the differences and relationships were clarified by the psychophysiological indices, and the measurement method was effective for evaluating clothing comfort sensation. The effectiveness of conventional measurement methods and linear analysis were confirmed for evaluation of clothing comfort sensation. However, the results regarding the relationship between CVRR and the sensation of stuffiness revealed a non-linear relationship rather than a linear one. In Chapter

2, although linear analysis was useful for evaluating simple changes that are dynamic in terms of physical status (pre-rest, exercise, post-rest), complex methods such as non-linear analysis are more effective for minute changes in higher-order psychological sensations and physiological responses. This chapter also indicated the need for non-linear analysis.

In Chapter 3, the collection of data regarding the ANN analysis in Chapter 4 and the data structure were explained. Three types of undershirts with different material properties were constructed using hydrophilic fibers (cotton or rayon) and hydrophobic fiber (PP) to obtain various types of data. The psychological structures of clothing comfort sensations were analyzed when the samples were worn. The results revealed that when wearing a sample using PP with high moisture transport properties and air permeability, evaluation terms related to moisture transport properties and air permeability, such as sensations of stuffiness and stickiness, were selected as psychological factors that had a strong influence on clothing comfort sensation. In contrast, for the 100% cotton undershirt sample, which had a softness and higher thickness, mechanical evaluation terms such as sensation of softness and skin contact were selected as psychological factors. These results indicated that the psychological factors involved in the wearer's clothing comfort sensation changed with the material characteristics of the undershirt sample and perspiration. The data structure was confirmed before analysis using ANNs.

In Chapter 4, evaluation of clothing comfort sensation using ANNs was attempted using the data of psychophysiological response measurement to verify the effectiveness of this method. The evaluation results revealed that it was possible to predict the clothing comfort sensation from an unknown data set with an accuracy of up to 85% when both the physiological response indices and psychological sensation data were used as the input data. These results suggested that it is important to measure both physiological and psychological aspects when evaluating clothing comfort sensation because the accuracy of the input conditions was lower when only psychological data or physiological response data were included separately. Comparison of the ANN findings with the prediction results of multiple regression analysis (a conventional linear analysis method) revealed that the ANN analysis was more accurate. These results indicated that the evaluation method using an ANN with psychophysiological response data was useful as a new technique for evaluating clothing comfort sensation.

Thus, the effectiveness of the evaluation method was verified for assessing the clothing comfort sensation using ANN as a first step. Additionally, the importance of measuring both physiological responses and psychological sensations was confirmed. The current findings may enable the development of more accurate and effective evaluation methods for clothing comfort sensation in the future.

Although the effectiveness of the method using ANN was verified, the current experiments involved several limitations that should be considered.

1. The results of the study were obtained using data from nine Japanese male college students.
2. Because there were only 128 data points in total, the ANN model did not perform deep calculations. Small-scale hierarchical neural networks were used in this thesis.
3. The ANN had a simple hierarchical structure for inputting raw data. The multivariate data were not analyzed before inputting, and other non-linear analysis methods were not examined.
4. Regarding the sample data, there were no data on the material properties corresponding to each participant’s condition at the same time, so the name number (PP/R/C; [1,0,0], PP/C; [0,1,0], C; [0,0,1]) was used.

There are several possible future research directions for addressing these limitations. First, it would be useful to collect data in female participants, and samples that include a wide range of ages and nationalities, to build a model that predicts the clothing comfort sensation from diverse physiological and psychological responses in future. Second, it may be valuable to include a larger number of samples and material data collected while clothing is worn as input data. The measurement of complex physical characteristics, such as the transport of heat and moisture and the skin contact state in real time at the time of wearing, would enable material and physical property data to be included in the ANN model. Thus, the proposed method for evaluating clothing comfort sensation can be improved in future studies. Additionally, it will be possible to prepare a larger amount of wearing data in the future using computer technology and measurement methods for physiological responses. The ANN model can also use other sources of information, including individual age, physical information, cultural attributes, and material information about fabrics, yarns, fibers as input data (shown in Figure 5.1). It will be possible to improve accuracy by examining the method and verifying its accuracy under various input conditions, and to improve accuracy and practicality by combining this approach with other non-linear analysis methods. The current approach may contribute to the development and manufacturing of undershirt products that consider each individual wearer.

The current findings suggest that ANNs may also provide a better tool for understanding clothing comfort sensation, which is a complex and higher-order sensation, as well as a tool for improving accuracy for the purpose of developing comfortable products. The current thesis verified a method for evaluating clothing comfort sensation using ANNs. The findings enabled examination of the relationships between output results (clothing comfort sensation) and input data (psychophysiological responses) by changing input amounts. Therefore, when the input amount is increased by various types of data, it is possible to deeply investigate the relationship between the clothing comfort sensation and the input data from the output results. It is possible that the ANN approach examined in this thesis could be used to analyze the relationships between clothing comfort sensations and other physical stimuli, lower-order sensations, and physiological responses, which cannot be understood using conventional linear analysis alone.

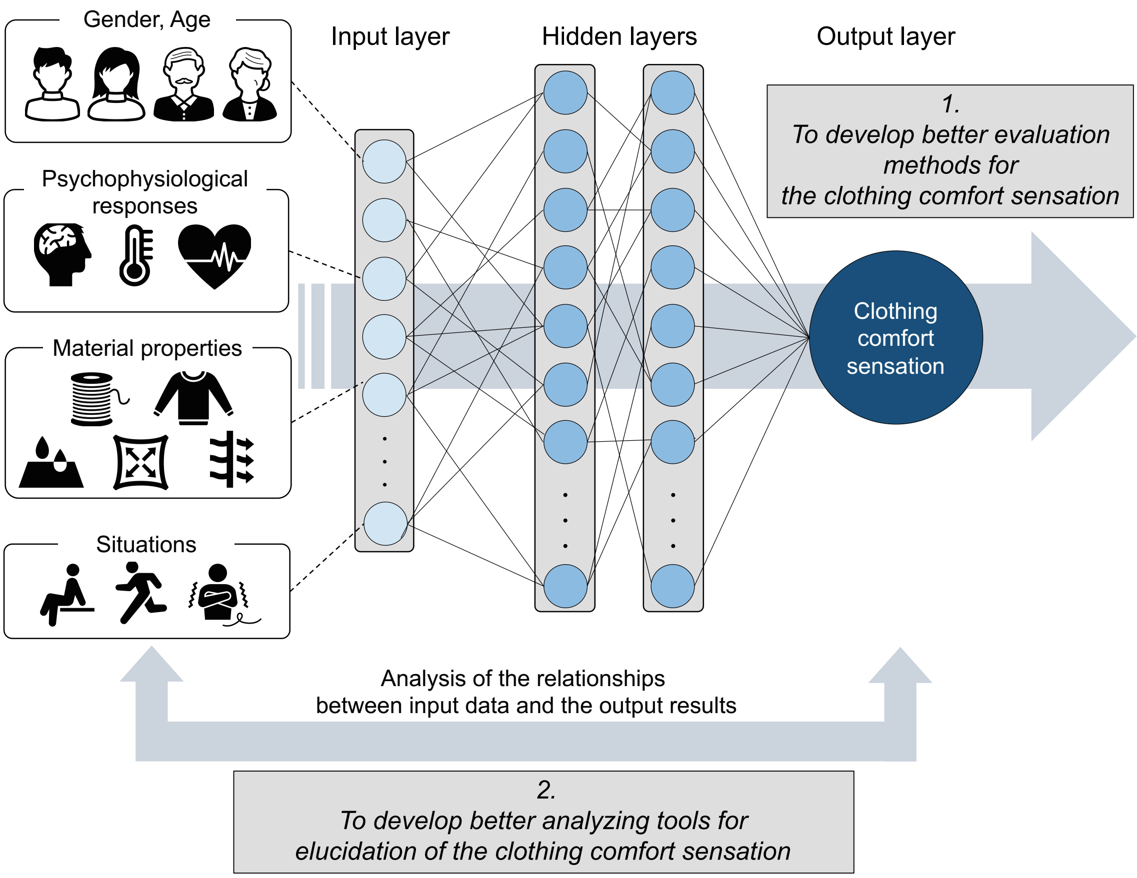


Figure 5.1. Future research directions suggested by the current findings

However, when large amounts of input information are used, humans may have difficulty understanding the output results for each condition. When parameters are used with a large amount of data, each neuron passes through several layers and performs complicated numerical analyses, and it becomes impossible to easily determine the important factors and relationships between input data and output results. Therefore, the development of techniques to explain the black box model, such as ANNs, and to clarify the important input features that contribute to the output result, may be useful for improving ANN analysis in future. With the development of these technologies, ANNs will provide a better tool for understanding the complex phenomenon of clothing comfort sensation.

References

1. Tamura T. Climate and Clothing. Japanese Journal of Biometeorology 2012; 49(2): 61–70.
2. O'Sullivan N, Teasdale DM, Mattiangeli V, Maixner F, Pinhasi R, Bradley DG and Zink A. A whole mitochondria analysis of the Tyrolean Iceman's leather provides insights into the animal sources of Copper Age clothing. Scientific Reports 2016; 6: 31279.
3. Li Y. The science of clothing comfort. Textile progress 2001; 31(1–2): 1–135.
4. Slater K. Human comfort. Volume 2. Springfield, IL, Thomas Publisher, 1985.
5. Mukhopadhyay A and Midha VK. A review on designing the waterproof breathable fabrics part II: construction and suitability of breathable fabrics for different uses. Journal of Industrial Textiles 2008; 38: 17–41.
6. Hatch KL. Textile science. West Publishing Company, 1993.
7. Wong A, Li Y and Yeung KW. Statistical simulation of psychological perception of clothing sensory comfort. Journal of Industrial Textiles 2003; 93, 108–119.
8. Kaplan S and Okur A. The meaning and importance of clothing comfort: a case study for Turkey. Journal of Sensory Studies 2008; 23: 688–706.
9. Edwin K, Yongchun Z, Josphat IM and Salome K. The Comfort Dimension; a Review of Perception in Clothing. Journal of Sensory Studies 2013; 28: 423–444.
10. Kaplan S and Okur A. Determination of coolness and dampness sensations created by fabrics by forearm test and fabric measurements. Journal of Sensory Studies 2009; 24: 479–497.
11. Kawabata S. The standardization and analysis of hand evaluation (2nd edition). Hand Evaluation and Standardization Committee, The Textile Machinery Society of Japan, 1980.
12. Kawabata S. Development of device for measuring heat moisture-transfer properties of apparel fabrics. Journal of the Textile Machinery Society of Japan 1984; 37: 130–141.
13. Kawabata S. Development of autonomic air-permeability tester. Journal of the Textile Machinery Society of Japan 1987; 40: 59–67.
14. Havenith G, Holmér I and Parsons K. Personal factors in thermal comfort assessment: Clothing properties and metabolic heat production. Energy Buildings 2002; 34: 581–591.
15. Winslow C.E.A, Herrington LP and Gagge AP. Physiological reactions of the human body to varying environmental temperature. American Journal of Physiology 1937; 120: 1–20.
16. Parsons K. Human Thermal Environments: The Effects of Hot, Moderate and Cold Environments on Human Health, Comfort and Performance. CRC Press, Taylor and Francis, 1993.
17. Sato M, Nakagawa M, Tokura H, Zhang P and Gong RH. Physiological effects of outerwear moisture transfer rate during intermittent bicycle exercise. Journal of the Textile Institute 2007; 98(1): 73–79.
18. Ha M, Tokura H, Yanai Y, Moriyama T and Tsuchiya N. The effects of fabric air permeability and moisture absorption on clothing microclimate and subjective sensation in sedentary women at cyclic

changes of ambient temperatures from 27 degrees C to 33 degrees C. Journal of Human Ergology 1999; 28(1–2): 1–13.

19. Horiba Y, Kamijo M, Hosoya S, Sadoyama T, Shimizu Y and Shimizu H. Evaluation of Thermesthesia for Wearing by Using Chaotic Analysis of EEG. Sen'i Gakkaishi 1999; 55(9): 440–446.
20. Horiba Y, Kamijo M, Hosoya S, Takatera M, Shimizu Y and Sadoyama T. Evaluation of tactile sensation for wearing by using event related potential. Sen-I Gakkaishi 2000; 56: 47–54.
21. Takanori Y. Nouha no sokutei to tyakuyoukan hyouka (in Japanese). Journal of the Textile Machinery Society of Japan 2000; 53: 103–107.
22. Matsudaira M, Takano S and Asou N. Shinpaku hendou supekutoru kaiseki ni yoru pajama no tyakuyou kaitekikan ni kansuru kentou (in Japanese), Journal of the Japan Research Association for Textile End-Uses 1999; 40(2): 115–119.
23. Mizuhashi H, Kamijo M, Yoshida H and Kubo M. Evaluation of thermal wearing comfort of undershirt made by blended yarn with polypropylene. Journal of Fiber Science and Technology 2016; 72(10): 220–226.
24. Ishimaru S. Study on Relationship Between Psychological Condition and Physiological Measurement, and Tactile. Journal of the Japan Research Association for Textile End-Uses 2006; 47: 772–784.
25. Stanislas D. The neural basis of the Weber–Fechner law: a logarithmic mental number line. Trends in Cognitive Science 2003; 7(4): 145–147.
26. Stevens JC and Stevens SS. Brightness Function: Effects of Adaptation. Journal of Optical Society of America 1963; 53(3): 375–385.
27. Leonard J, Pirotte F and Knott J. Classification of second hand textile waste based on near infrared analysis and neural network. Melliand International 1998; 4: 242–244.
28. She FH, Kong L, Nahavandi S and Kouzani A. Animal fibre classification. Textile Asia 2001; 32(1): 44–47.
29. Jasper WJ and Kovacs ET. Using neural networks and NIR spectrophotometry to identify fibers. Textile Research Journal 1994; 64: 444–448.
30. Pynckels F, Kiekens P, Sette S, Langenhove VL and Impe K. Use of neural nets for determining the spinnability of fibres. The Journal of The Textile Institute 1995; 86: 425–437.
31. Ramesh MC, Rajamanickam R and Jayaraman S. The prediction of yarn tensile properties by using artificial neural networks. The Journal of The Textile Institute 1995; 86: 459–569.
32. Cheng L and Adams DL. Yarn strength prediction using neural networks- Part 1: fibre properties and yarn strength prediction. Textile Research Journal 1995; 65: 495–500.
33. Fan J and Hunter L. A worsted fabric expert system. Part II: an artificial neural network model for predicting the properties of worsted fabrics. Textile Research Journal 1998; 68: 763–771.
34. Ertugrul S and Ucar N. Predicting bursting strength of cotton plain knitted fabrics using intelligent techniques. Textile Research Journal 2000; 70: 845–851.

35. Ishii M, Takeuchi Y and Kimura C. Construction of small scale hierarchy neural network for clothing comfort evaluation of skirt. Journal of the Japan Research Association for Textile End-Uses 2005; 46: 439–446.
36. Wong ASW, Li Y, Yeung PKW and Lee P.W.H. Neural network predictions of human psychological perceptions of clothing sensory comfort. Textile Research Journal 2003; 73: 31–37.
37. Wong ASW, Li Y and Yeung PKW. Predicting clothing sensory comfort with artificial intelligence hybrid models. Textile Research Journal 2004; 74: 13–19.
38. Oosemans J, Hermans B and Puers R. Integrating wireless ECG monitoring in textiles. Sensors and Actuators A: Physical 2006; 130: 48–53.
39. Cho G, Jeong K, Paik M.J, Kwun Y and Sung M. Performance evaluation of textile-based electrodes and motion sensors for smart clothing. IEEE Sensors Journal 2011; 11(12): 3183–3193.
40. Japanese Industrial Standard, JIS L 0105: 2020.
41. BOKEN. Official website, https://www.boken.or.jp/find_items/textile/clothing/functionality_clothing/1264/ (accessed 12 August 2021).
42. Karasawa Y, Uemae M, Yoshida H and Kamijo M. Investigation on psychological structure of wearing comfort sensation of undershirt made of yarn blended with polypropylene. The proceedings of the 4th International Symposium on Affective Science and Engineering 2018; 1–5.
43. Hessemer V and Bruck K. Influence of menstrual cycle on shivering, skin blood flow, and sweating responses measured at night. Journal of Applied Physiology 1985; 59: 1902–1910.
44. Stephenson LA and Kolka MA. Menstrual cycle phase and time of day alter reference signal controlling arm blood flow and sweating. American Journal of Physiology 1985; 249: 186–191.
45. Stening K, Eriksson O, Wahren L, Berg G, Hammar M and Blomqvist A. Pain sensations to the cold pressor test in normally menstruating women: comparison with men and relation to menstrual phase and serum sex steroid levels. American Journal of Physiology 2007; 293: 1711–1716.
46. Del CJ, Estevez E and Mora RR. Caffeine during exercise in the heat: thermoregulation and fluid electrolyte balance. Medicine & Science in Sports & Exercise 2009; 41: 164–173.
47. Kelly G. Body temperature variability (Part 1): a review of the history of body temperature and its variability due to site selection, biological rhythms, fitness, and aging. Alternative Medicine Review 2006; 11: 278.
48. Konica Minolta. Official website, https://www.konicaminolta.com/jp-ja/runpro/running/sports_safety/004.html (accessed 13 August 2021).
49. Kuroko N and Fujii E. An experimental study of noise stress recovery by inspecting green spaces using electroencephalogram, heart rate and subjective evaluation. Journal of the Japanese Institute of Landscape Architecture 2002; 65(5): 697–700.
50. Pagani M, Lombardi F, Guzzetti S, Rimoldi O, Furlan R, Pizzinelli P, Sandrone G, Malfatto G,

Dell'Orto S and Piccaluga E. Power spectral analysis of heart rate and arterial pressure variabilities as a marker of sympatho-vagal interaction in man and conscious dog. Circulation Research 1986; 59: 178–193.

51. Tamura T and Koshiba T. Humidity sensation of human body, Part I: General humidity sensation. Journal of the Japan Research Association for Textile End-Uses 1995; 36(1): 125–131.
52. Liu W, Lian Z and Liu Y. Heart rate variability at different thermal comfort levels. European Journal of Applied Physiology 2008; 103: 361–366.
53. Ushioda H, Fukuda M. A study on the development of clothing that causes the positive comfortable sense. Descent Sports Science 2000; 21: 146–156.
54. Yamazaki K, Suga S, Kuwahara K, Hamamda Y, Syu S, Nakano R, Kobayashi K and Takahashi N. Effect of simulated work in artificial climate chamber on physiological and psychological responses of construction workers with air-conditioned wear. Journal of Environmental Engineering (Transactions of AIJ) 2018; 83(748): 543–553.
55. Mizuhashi H, Kamijo M, Yoshida H and Kubo M. The effect of mixing ratio against material properties of knitted fabric made by blended yarn with polypropylene and cotton. Journal of Fiber Science and Technology 2017; 73(3): 75–81.
56. Ramanathan NL. A new weighting system for mean surface temperature of the human body. Journal of Applied Physiology 1964; 19: 531–533.
57. Srivastava N, Hinton G, Krizhevsky A, Sutskever I and Salakhutdinov R. Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research 2014; 15(1): 1929–1958.
58. Richard HR H, Sarpeshkar R, Mahowald AM, Douglas JR and Seung SH. Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit. Nature 2000: 405; 947–951.
59. Kingma DP and Jimmy BA. Adam: A method for stochastic optimization. Proceedings of the 3rd international conference for learning representations (ICLR 2015) 2015: arXiv:1412.6980.
60. Gemperline PJ, Long JR, Gregoriou VG and Chem A. Nonlinear multivariate calibration using principal components regression and artificial neural networks. Analytical Chemistry 1991; 63: 2313.
61. Liu R and Little T. The 5ps model to optimize compression athletic wear comfort in sports. Journal of Fiber Bioengineering and Informatics 2009; 2: 41–52.
62. Harada T. Main factors affecting wear comfort on the field tests. Journal of the Textile Machinery Society of Japan 1983: 36(4); 212–217.
63. François C. Deep Learning with Python. Manning, 1973.
64. Custodio V, Herrera FJ, López G and Moreno JI. A review on architectures and communications technologies for wearable health-monitoring systems. Sensors (Basel) 2012; 12(10): 13907–13946.

Presented papers

This thesis was composed by these papers with referee system.

1. Karasawa Y, Uemae M, Yoshida H and Kamijo M. Effectiveness of a method of evaluating the clothing comfort sensation in a perspiration state by measuring psychophysiological responses. International Journal of Affective Engineering 2020; 20(1): 21–31.
2. Karasawa Y, Uemae M, Yoshida H and Kamijo M. Investigation on psychological structure of wearing comfort sensation of underwear made of yarn blended with polypropylene. Proceedings of the 4th International Symposium on Affective Science and Engineering 2018; 1–5.
3. Karasawa Y, Uemae M, Yoshida H, Kamijo M, Mizuhashi H, Nishiyama T and Masahiko Kubo. Evaluation of Thermal-Moisture Comfort sensation of Underwear Made of Yarn Blended with Polypropylene by Measuring Psychological/Physiological Responses. Proceedings of the 11th Textile Bioengineering and Informatics Symposium Advanced Materials and Smart Wearables 2018.
4. Karasawa Y, Uemae M, Yoshida H and Kamijo M. Prediction of clothing comfort sensation of an undershirt using artificial neural networks with psychophysiological responses as input data. Textile Research Journal 2022; 92(3–4): 330–345.

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