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Development of a human metabolic rate prediction model based on the use of Kinect-camera generated visual data-driven approaches

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ABSTRACT

Predicting thermal comfort is one of the primary building research domains due to its technical and environmental significance. A metabolic rate, one of the significant variables for predicting an individual's thermal comfort, is primarily based on the human body's activity level. While other human and environmental factors, such as air temperature and relative humidity are easily measured and collected, with the help of sensory devices, a metabolic rate varies with time, and is not easy to measure to determine an accurate thermal comfort estimation in reality. Therefore, this study investigated the potential use of Deep Learning algorithm to accurately estimate the metabolic rate for a better thermal comfort estimation. A series of chamber tests were conducted with 23 test participants. The Kinect sensor was adopted to detect a user's physical motion, by capturing the motion images. With the help of a wearable sensor, a user's heart rate was also measured to estimate a metabolic rate.

This study found that males showed higher MET than females, and the high BMI group generated higher MET than the low BMI group. The result also indicated that an estimated accurate range of 77%–89% was reasonably acceptable in the self-MET prediction modeling, while it was 65% in the third-party MET prediction. Therefore, the outcome of this research confirms that it is possible to use the Kinect sensor as a remote sensing device to estimate a user's metabolic rate, based on the use of a Deep Learning algorithm developed per individual.

1. Background

As modern people spend more than 90% of their time indoor [1], many health-conscious people have demanded better indoor environment quality (IEQ) in their ambient condition [2]. Among the elements of IEQ, an environmental thermal comfort (TC) has been reported as a most significant element that affects the user's work efficiency and productivity as well as environmental health [3,4].

TC is determined by environmental factors, such as air temperature, relative humidity, air speed, and radiation temperature, and personal factors, which consist of clothing condition (Clo) and metabolic rate (MET) [5,6]. Those environmental factors are easily measured by environmental sensors, while human factors are relatively difficult to predict or measure because of various conditions depending on individuals' environmental preferences/needs. Among those factors, a MET changes TC significantly according to physical activity, such as sleeping, resting, exercising, etc. [7]. According to Kosonen et al. [8], the comfortable range of PMV (predicted mean vote), considered as a TC index, is between −0.5 and + 0.5 [9]. The assumed activity within the comfort range is 1–1.5 METs at the condition of MRT: 24.5 °C; air speed: 0.1 m/s; RH: 50%; temperature: 25 °C; and Clo 0.5. Therefore, even a minor change in MET, generated in activity could contribute to a large variation in estimating the TC condition.

Recently, there have been many research efforts that developed a data-driven TC model based on the use of real-time thermal sensation vote (TSV) data from individuals. However, these studies still heavily rely on an assumed MET without considering an actual MET of the user [10]. According to Luo et al. [11], a MET is the most important parameter in relation to TC, but it is still the most crudely evaluated among the six thermal comfort components in the research and application areas.

Because the evaluation of MET in the field of sports & medicine has a direct impact on human health based on energy expenditure, considerable research has been conducted using various methods. Bouten C. V et al. [12] used a triaxial accelerometer to analyze the relationship between energy expenditure and physical activity. Sedentary activities

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Table 1
Levels for the determination of the metabolic rate [25].

Level	Method	Accuracy	Inspection of the workplace
(1) Screening	1A: Classification according to occupation 1B: Classification according to activity	Rough information; very great risk of error	Not necessary, but information needed on technical equipment, work organization
(2) Observation	2A: Group assessment tables 2B: Tables for specific activities	High error risk accuracy: ± 20%	Time and motion study necessary
(3) Analysis	Heart rate measurement under the defined conditions	Medium error risk accuracy: ± 10%	Study required to determine a representative period
(4) Expertise	4A: Measurement of oxygen consumption 4B: Doubly labeled water method 4C: Direct calorimetry	Error within the accuracy limits of the time and motion measurement: ± 5%	Time and motion study necessary Inspection of workplace not necessary, but leisure activities must be evaluated Inspection of workplace not necessary

and walks on a motor-driven treadmill (3–7 km.h-1) were conducted. The results of this study are as follows: When all the directions (IAAtot) were measured, the accelerometer output found (r = 0.95, P & lt; 0.001, Sy, x = 0.70 W.kg-1).

Staudenmayer, J et al. [13] developed an artificial neural network (ANN) to estimate the physical activity energy expenditure and identify the physical activity type with an accelerometer. Subject activities were of varying intensities, sedentary, light, moderate, and vigorous; each activity was conducted for 10 min. In this study, K4b^2 ™ was used to measure oxygen consumption to calculate MET. Even though these precise MET assessment methods have been developed in various research fields, according to Ravussin et al. [14], the MET has seen minimal focus in the construction research area in spite of its significant impact on thermal comfort. The reason is it is difficult to measure MET with some simple sensors [15]. Precise measurements can be obtained only by the use of a complicated and expensive device [14]. There are some efforts to measure MET in construction field, especially using a wearable sensory device, but the collection process should be integrated with a real-time sensing system and also could be practically limited [16]. Luo et al. [11] evaluated MET for TC by recording their study subjects' daily life activities. Ruiz et al. also proposed a method involving the calculation of the indoor concentration ratio using the CO_2 sensor for indoor air quality evaluation and MET prediction [17,18]. Although various prediction methods are emerging, individual predictions are still technically limited, and that the prediction accuracy is considerably low.

Thus, it is necessary to find a way of predicting individual METs in high accuracy with consideration of the practical application. Therefore, this study developed a prediction model of METs with the help of integrated algorithms of Artificial Intelligence (AI) [17,19]. AI is widely used throughout the industry, along with Deep Learning, especially in various building research fields [20–23]. For example, Vakalopoulou et al. used an AI technique, deep convolutional neural networks (DCNN), to interpret the satellite images into building geometries, and adopted this method for urban planning. Marino et al. proposed a new energy load prediction methodology for buildings through deep neural networks (DNNs). Fan et al. used deep learning to predict the cooling load of a building 24 h in advance and obtained better prediction results compared with the conventional statistics-based model. Therefore, an AI-adopted estimation has a high potential to address intractable problems in the thermal comfort research domain.

Recently, in the area of computer science, a behavior recognition technology has been developed that utilize visual images captured by a camera (e.g., Kinect camera) to extracts an actual behavioral information [24]. These data are frequently integrated with many computational processes, especially for a computer game, virtual reality, and motion detection. Therefore, this study exploits the currently developed computational sensing technology, e.g., Kinect sensor, to collect and process a building user's behavioral information in order to develop an accurate MET prediction model as a function of users' graphical data-driven principle. Considering the technical compatibility with the Kinect camera, this study developed one of Deep Learning algorithm, called HRNet for an effective TC estimation.

Overall, methods for accurately measuring MET in various research areas such as sports and medicine are expensive and impractical. In the architectural field, the various methods for measuring MET have been approximative and not tailored to the individual. Our research was conducted to overcome these weaknesses. The contributions of our research are as follows:

First, a method that enables individual MET prediction for a better thermal comfort (TC) in the field of architecture. Second, unique behaviors of the occupant can be predicted using the Kinect camera. Third, the MET measurement through a low-cost wearable device can help determine the TC required in the construction field without requiring any expensive equipment. Finally, the MET prediction can be performed without any wearable devices using deep learning.

2. Methodologies

2.1. Metabolic rate evaluation

2.1.1. Metabolic rate evaluation methods

The international standard ISO 8996 classifies the MET measurement methods into four levels based on the suggested accuracy, as summarized in Table 1. This standard was adopted in this study to estimate a MET as a function of heart rate.

This method assumes that average information, such as age, weight, and height is applied to establish international standards, as shown below [11].

- a male: 30 years old; 1.75 m high; and weighing 70 kg (1.8 m^2 body surface area)
- a female: 30 years old; 1.70 m high; and weighing 60 kg (1.6 m^2 body surface area)

Levels 1 (screening) and 2 (observation) show only the approximate MET values and do not consider the individual characteristics. Thus, the error risk is considerably high. The approximate MET is easier to judge, however, because the method is intuitive and easy to understand. Detailed of Levels 1 and 2 are summarized in Table 2.

The Level 3 MET measurement method predicts a MET based on the measured heart rate in real time. According to Strath et al., a heart rate has a significant relationship with a MET. That is, in a normal-climate environment, a human body's heart rate changes according to his physical activity level [26]. This relationship has been applied to estimate a MET by estimating an oxygen consumption rate according to the heart rate change. The Level 3 MET measurement method [27] has the disadvantage of omitting the psychological factors, but its error rate less than 10%, and its accuracy is much higher than that of the Level 1 and 2 methods. Therefore, the Level 3 method, with an easier measurement, was adopted for measuring a MET in this study.

Table 2
Metabolic rate for specific activities [25].

Activity	W/m-2
Sleeping	40
Reclining	45
At rest, sitting	55
At rest, standing	70
Walking on a level, even solid path	
Without a load, at 2 km·h-1	110
With a 10 kg load, 4 km·h-1	185
Sedentary activity (office, dwelling, school, laboratory)	70
Standing, light activity (shopping, laboratory work, light industry)	95
Standing, medium activity (shop assistant work, domestic work, machine work)	115

The level 4 MET measurement method measures the MET by directly calculating the oxygen or energy consumption. It is the most accurate method but demands more complicated and extremely high-resolution sensing devices. In addition, this method is more appropriate in a laboratory experiments setting, rather than a dynamic condition, which this study assumed with consideration of general daily life in a general built environment.

Therefore, this study adopted the Level 3 MET measurement method. Table 3 summarizes the physiological settings that this study adopted to estimate a MET based on the use of heart rate collected in real time during the user study.

2.1.2. Review the applicability of level 3 method

In fact, the use of the level 3 MET method using heart rate (HR) for indoor activity requires great caution. According to ISO 8996-2004, the recommendation is to use a HR of 120 beats per minute (bpm) or higher when predicting MET. In addition, the low range in HR suggests that the accuracy of the MET prediction is quite low. Indeed, in this low range, various factors such as psychological, thermal environmental, respiratory effects, circadian rhythms, and dehydration can interfere. Therefore, we must verify that level 3 MET method is appropriate for the low-level MET evaluation of exercises such as indoor activities. According to the WHO report [28], "It is possible to use a general equation to estimate energy expenditure (EE) which is proportional to MET at low activity levels (Under 3 METs), but the estimate is inaccurate." [29] Thus, MET prediction using heart rate at low activity levels is possible albeit with low accuracy.

Takken et al. evaluated activity energy expenditure (AEE) through heart rate for 63 children with different types of chronic diseases [30]. Thus far, activities in the experiments were: resting protocol, working on a computer, sweeping, hallway walking, steps, and treadmill walking at three different speeds. Among these activities, resting protocol, and working on the computer activity are linked to low levels in the heart rate range similar to that of (1) Lying down (2) Sitting (watching TV) in our experiment. Therefore, a MET evaluation using this low level of heart rate in our research is also possible.

Eston et al. [31] conducted an experiment to compare the predictive accuracy of AEE using HR, pedometry, and accelerometry for 30 children. Crayoning, catch, hopscotch and walking were conducted as part of the experiment. The crayoning activity used in this experiment was related to a significantly lower heart rate range. It was also considered to be a reliable result.

As a result, we are predicting MET to evaluate TC in architectural aspects. High precision predictions may not be that relevant due to the various effects of the six factors (MET, Clo, air temperature, relative humidity, air speed, and radiation temperature). Finally, we conclude by stating that using HR as a method of evaluating MET is an optimal method in terms of practicality, cost-effectiveness, and availability albeit at the cost of relatively low accuracy.

2.2. Experimental methods

2.2.1. Flowchart

As shown in Fig. 1, there are three levels: the learning, system, and prediction levels. First, images are obtained by sensing the human's activities using a Kinect camera at the learning level. At the same time, the heart rate data are collected through a wearable device (Fitbit Charge2™). Using the collected heart rate data. Second, at the system level, Deep Learning is performed on the heart rate values and images obtained through the Kinect camera. Third, at the prediction level, the human heart rate can be predicted based only on the real-time image information obtained through the Kinect camera, without the information provided by the wearable device. Finally, through the unchanged information of the experimenter (gender, weight, and age) and the heart rate which was predicted, the MET is calculated according to the above-described level 3 MET estimation method.

Fig. 2 illustrates how to collect a heart rate data from individual test participants during the test. First, during the deep learning phase, the test participants were observed using a Kinect camera while the heart rates were measured by the test participants' wearable device (Model: Fitbit Charge 2™).

2.2.2. Experiment equipment

This study adopted a series of user studies based on the use of multiple sensory devices to measure a test participant's physiological information and his/her ambient environmental conditions, as summarized in Table 4. First, the Kinect camera senses the motion and judges the simple image information and the depth information of the image so that accurate information can be obtained in three dimensions. Also, the movements of 20 human body joints/segments can be

Table 3
Relationship between metabolic rate (in W/㎡) and heart rate (in beats per min) [25].

Age	Weight (kg)				
Female	50 kg	60 kg	70 kg	80 kg	90 kg
20	2,9 × HR − 150	3,4 × HR − 181	3,8 × HR − 210	4,2 × HR − 237	4,5 × HR − 263
30	2,8 × HR − 143	3,3 × HR − 173	3,7 × HR − 201	4,0 × HR − 228	4,4 × HR − 254
40	2,7 × HR − 136	3,1 × HR − 165	3,5 × HR − 192	3,9 × HR − 218	4,3 × HR − 244
50	2,6 × HR − 127	3,0 × HR − 155	3,4 × HR − 182	3,7 × HR − 207	4,1 × HR − 232
60	2,5 × HR − 117	2,9 × HR − 145	3,2 × HR − 170	3,6 × HR − 195	3,9 × HR − 219
Male	50 kg	60 kg	70 kg	80 kg	90 kg
20	3,7 × HR − 201	4,2 × HR − 238	4,7 × HR − 273	5,2 × HR − 307	5,6 × HR − 339
30	3,6 × HR − 197	4,1 × HR − 233	4,6 × HR − 268	5,1 × HR − 301	5,5 × HR − 333
40	3,5 × HR − 192	4,0 × HR − 228	4,5 × HR − 262	5,0 × HR − 295	5,4 × HR − 326
50	3,4 × HR − 186	4,0 × HR − 222	4,4 × HR − 256	4,9 × HR − 288	5,3 × HR − 319
60	3,4 × HR − 180	3,9 × HR − 215	4,5 × HR − 249	4,8 × HR − 280	5,2 × HR − 311

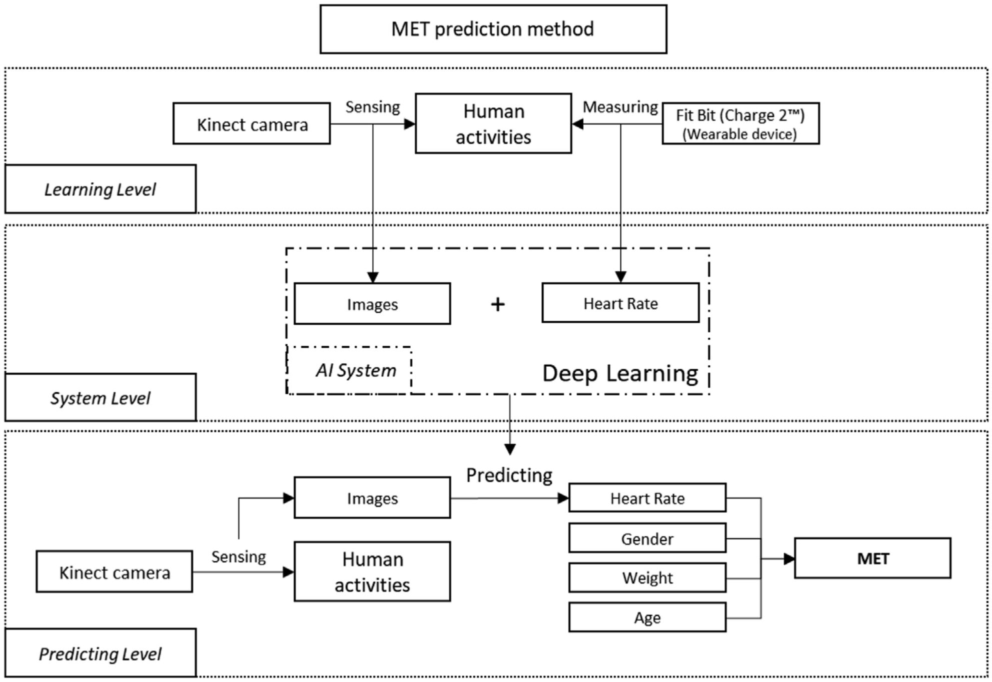


Fig. 1. Flowchart of MET estimation.

tracked to perceive them more accurately. For this reason, the Kinect camera has been actively used in many research fields requiring a human perception [32,33].

Fitbit's Charge 2™ was used to measure the heart rate, which has been validated by adopting in many research projects in academia [34,35]. Testo 480 was used to measure environmental parameters, which include temperature, humidity, air velocity, and radiation temperature. CO_2 concentration was measured to monitor any change of CO_2 concentration in the test chamber. A ventilation rate was controlled to keep the chamber's air quality condition consistent and below 1000 PPM was maintained as suggested by the ASHRAE 62.1 Indoor Air Quality Guidelines [36].

2.3. Deep learning

To establish a robust MET prediction model, this study adopted a Deep Learning algorithm a heart rate network (HRNet). Recent studies on image understanding and machine learning have focused on the use of hand-crafted features including a histogram of oriented gradients (HOG) [41] and scale-invariant feature transforms [42]. The features created by human beings, however, have limitations in expressing images. Convolutional neural network (CNN) [43], a primary method of deep learning that has been widely employed in the field of machine learning of late, has been developed for mathematically optimized features to improve the image representation. For extending the network, we propose a heart rate network (HRNet), a vision-based non-contact heart rate prediction technique that utilizes the deep network in each video frame. The appearance information was analysed through the deep network, and it could come up with predictions close to the actual heart rate according to human activity.

The appearance information is a critical clue that characterizes a human activity behavior being extracted from a captured video. The behavior is an essential factor closely related to a person's heart rate. Through the adopted HRNet, the appearance features of a human body and the surrounding objects are extracted from the test subject's motion from each video frame. In this study, the AlexNet [43] model pre-trained on the ImageNet [44] dataset was extended, and the model on the heart rate dataset was fine-tuned. As shown in Fig. 3, HRNet uses the RGB value of each pixel of the input image as the input data. The proposed HRNet consists of eight layers: the first five convolutional layers and the following three fully connected layers. The first convolutional layer (Conv1) performs rectified linear unit, local response normalization and max-pooling with a $11 \times 11 \times 96$ (filter width x filter length x number of filters) filter.

A rectified linear unit (ReLU) is an activation function that reduces the gradient vanishing problem of a non-saturating nonlinearity and is expressed mathematically as $f(x) = \max(0, x)$. Local response normalization (LRN) performs normalization of the feature response, the output of ReLU, as shown in the equation below.

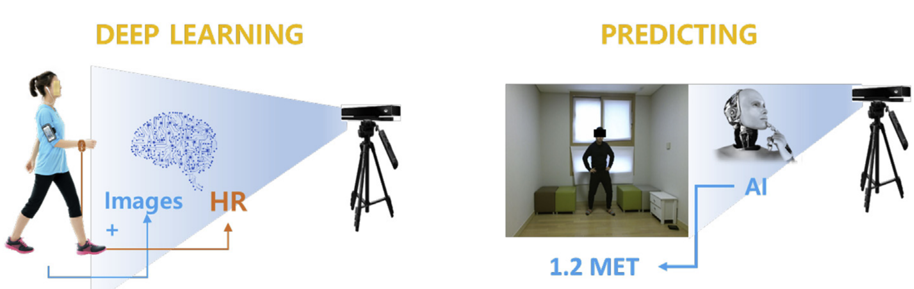
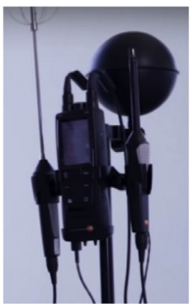


Fig. 2. Learning and prediction method.

Table 4
MET measurement devices.

Device name images	Basic principle and condition	Device name images	Basic principle and condition
Kinect camera [37–39] 	Motion-sensing device; simple image information + depth information; movements can be read by tracking the joints of each person	Fitbit Charge 2™ [34,35] 	Measures the human heart rate in real time; stores data in 5-s increments
Testo480 [40] 	Identifies the PMV elements in the laboratory (temperature, humidity, air speed, radiation temperature)	TSI IAQ-CALC 	Measures the CO_2 concentration in real time to determine the effect of the MET due to the CO_2 concentration in the room

$$LRN_{x,y}^{i} = ReLU_{x,y}^{i} / \left(k + \alpha \sum_{j=\max\left(0,\, i-\frac{n}{2}\right)}^{\min\left(N-1,\, i+\frac{n}{2}\right)} \left(ReLU_{x,y}^{j} \right)^{2} \right)^{\beta} \tag{1}$$

n is the number of channels in the layer, and x, y are the spatial position in the feature map and the normalized sum of the squares of responses of n's adjacent positions from (x, y). The hyperparameters of k, n, α, and β were set to k= 2, n= 5, α= 10^{-4}, $\beta = 0.75$, as proposed in Ref. [43]. Max pooling (MP) selects the most significant value among the responses corresponding to the adjacent positions of the spatial position (x, y) as a feature response, and is used to reduce overfitting.

The second convolutional layer (Conv2) performs ReLU, LRN, and MP with a 5 × 5 × 256 filter. The third and fourth convolutional layers (Conv3, Conv4) perform ReLU with a 3 × 3 × 384 filter, and the fifth convolutional layer Conv5) performs ReLU and MP with a 3 × 3 × 256 filter. The sixth and seventh fully connected layers (FC6, FC7) are 4096-dimensional vectors and perform ReLU and dropout. Dropout (DP) is a regularization method for reducing the overfitting problem of the FC layer by fixing the hidden neuron output at 0 at a constant rate. The DP ratio that was utilized in this study was 0.5, as proposed in Ref. [43].

Finally, the eighth fully connected layer (FC8) is a scalar value that represents the expected heart rate through regression. After the last fully connected layer, the Euclidean loss between the predicted heart rate and the ground truth heart rate is calculated to learn the parameters of the entire network in a stochastic gradient descent with momentum (SGD) via the back-propagation scheme. The size of the input image to the network is 227 × 227 × 3. The specific hyperparameters for HRNet training are as follows. HRNet has a 64 mini-batch size, a 0.9 SGD momentum, a $5e^{-4}$ weight decay, a 40,000-step size for decreasing the learning rate, and a $1e^{-6}$ initial learning rate. The learning rate was reduced by 1/10 per step size, and the learning process was repeated up to 100,000 times.

2.4. Experiment conditions

This experiment was conducted in winter, from December 15th to 21st, 2017. Previous studies have shown that most of the people living in residential houses wear clothing with less than 1.0 Clo in winter

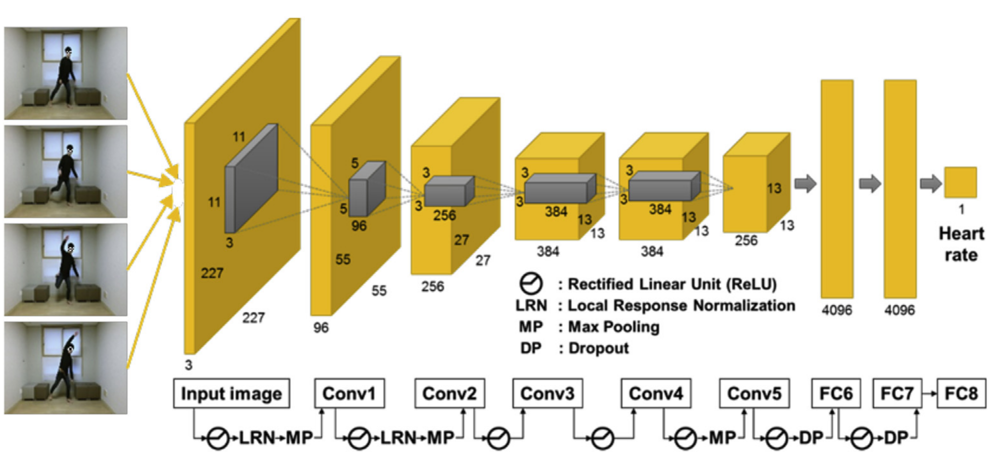


Fig. 3. Structure of the heart rate network (HRNet), a vision-based heart rate prediction model using deep learning.

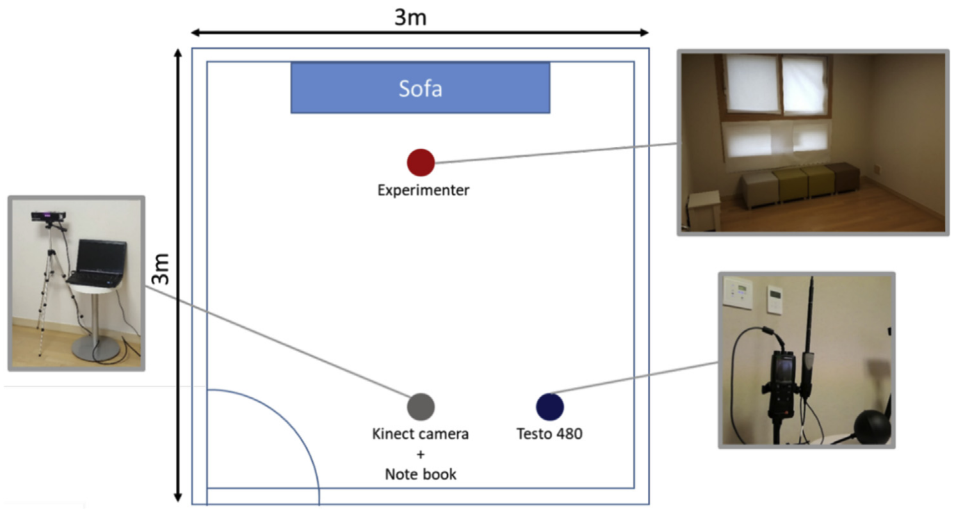


Fig. 4. Floor plan of the experiment room.

Table 5
PMV conditions of the experiment room.

Room	Air temperature (°C)	MRT (°C)	Relative humidity (%)	Air velocity (m/s)	PMV (1 MET)	PPD (%)
Condition	22.4 ± 1.06	22.7 ± 0.61	30.2 ± 4.24	0.02 ± 0.015	−0.28 ± 0.25	7.93 ± 5.88

[45,46]. Therefore, a laboratory attire of 0.75 Clo measured using a thermal manikin was prepared and tested. The experiment was conducted in the experiment room in the POSCO Green Building in Songdo, Incheon, Korea (Fig. 4). The temperature was maintained at 22.4 °C ± 1.06, and the relative humidity was around 30.2% ± 4.24 in the test chamber, and the estimated PMV conditions are summarized in Table 5.

A total of 23 subjects participated in the test. All the test participants were university students in their twenties. In the early stages of this study, the focus was on the impact of gender and BMI on MET prediction while intentionally removing the effect of age, viewed as an additional research parameter. Gender, age, height, weight, and BMI data were collected and are summarized in Table 6.

2.5. Experimental contents

The test participants were not allowed to eat for 3 h before the experiment to keep individual test participants' physical conditions consistent. Before they were made to enter the experiment room, it was ensured that the test participants had enough rest so that they would generate a stable heart rate. The experiments were conducted on four activities: lying down (sleeping), sitting (watching TV), stretching (yoga), and light exercise (aerobics). Heavy exercises (i.e., demanding a MET), such as soccer and basketball were excluded from this study because the experiments were intended for an indoor activity.

The activities were selected to proceed from those causing a low to high MET to minimize the impact of prior activities on MET. The data collected for 1 min before and after each activity were removed for clearly identifying the data dedicated to each activity. The experimental measurement time, training, and testing in Deep Learning are summarized in Table 7. Among the collected data, 70% of them were processed as a training dataset and the remaining 30% as a testing dataset. These two-formatted independent processed datasets were used for individuals' MET prediction (discussed in 3.2).

Table 6
Demographic information of the participants.

Participants	Total (23)	Male (14)	Female (9)
Age	21.9 (SD 2.6)	22.5 (SD 2.9)	21 (SD 1.7)
Height (cm)	168.6 (SD 6.4)	172.7 (SD 4.0)	162 (SD 2.8)
Weight (kg)	66.4 (SD 14.3)	74.3 (SD 12.0)	53.8 (SD 6.3)
BMI (kg/m^2)	23.3 (SD 3.9)	25.2 (SD 3.6)	20.4 (SD 2.3)

Lying down (sleeping): This is an indoor activity that generates the lowest MET. In this experiment, a subject was requested to be relaxed in this posture. The test participants were also provided enough rest time before the experiment.

Sitting (watching TV): Since one of the most common indoor activities is sitting and watching TV in reality, this study adopted this posture for one of the METs selected. The test participants were requested to watch TV while sitting on a couch or floor. To minimize any unwanted impacts on heart rate, such as psychological condition, each test participant was requested to keep for a stable psychological condition without thinking about any stressful condition.

Stretching (yoga): This posture is for mimicking an indoor exercise. The test participants were requested to watch a 15-min yoga video and to follow the movements therein.

Light exercise (aerobics): Aerobic exercise was chosen because it is the most dynamic indoor activity. The test participants watched a 15-min video and followed the movements therein. The aerobic exercise was limited to 15 min so as not to challenge the limits of the test participants' strength.

3. Results and discussion

3.1. Comparison of the actual METs according to gender and BMI

In the results and discussion section, the limitations of the MET assessment method using HR for low-level activities should be considered, as discussed in 2.1.2. It is critical to compare the estimated MET with the Standards defined in ASHRAE 55/ISO-8996 to see the accuracy of the prediction performance in this study. The test results showed there was a large discrepancy between the measured and the actual MET values at each corresponding activity level (which is defined by the ASHRAE 55 and ISO 8996) [25]. The errors were primarily caused by a significant number of outliers that were accidently

Table 7
Procedures followed for the experiments.

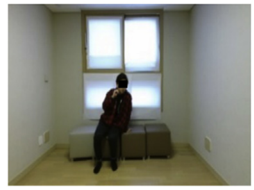
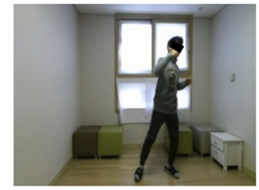
Activities				
	(1) Lying down (sleeping)	(2) Sitting (watching TV)	((3) Stretching (yoga)	((4) Light exercise (aerobics)
Measuring time (training dataset/ testing dataset)	30 min (20/8) min	30 min (20/8) min	15 min (10/3) min	15 min (10/3) min

Table 8
Mean METs by activity level and gender.

	(1) Lying down (sleeping)	(2) Sitting (watching TV)	(3) Stretching (yoga)	(4) Light exercise (aerobics)
Male	1.21 ± 0.5	1.34 ± 0.5	1.91 ± 0.6	4.49 ± 1.2
Female	1.09 ± 0.3	1.11 ± 0.4	1.55 ± 0.5	3.56 ± 1.1
(Male-female) mean value	0.12	0.23	0.36	0.93

generated during the environmental chamber test. It may be affected by multiple ambient environment or physiological conditions. According to Appelhans [49], a MET as a function of heart rate is significantly affected by the user's psychological condition, in addition to the physical activity level. Such a psychological condition could vary depending on individual test participants. Therefore, the outliers of the dataset were removed from the datasets by the removal method [50]. The error rates were significantly reduced with no outliers, and those accuracy rates are summarized in Table 8. In spite of the reduced error rates, the test results still have a discrepancy between the measured MET and the MET value defined in ASHRAE 55. However, since this study focused on technical findings to establish a data-driven metabolic rate prediction model by using human subject tests with consideration of human physiological factors, this section primarily discussed the correlations between gender Vs. MET, and BMI Vs. MET.

Since gender has been frequently discussed as one of the physiological parameters that affect thermal comfort and perception [47,48], it is necessary to analyze the measured actual MET by gender per activity level. Fig. 5 illustrates the comparison results of measured MET levels between the genders per activity based on the use of 2-sample T-test. It reveals that all the comparison sets are statistically significant with a p-value less than 0.001. In all the activity levels, the MET of the male showed higher values than that of the female. In addition, as the level of activity increased, the difference of the METs between the male and female groups became larger. As summarized in Table 8, there is a 0.12 MET difference found in the activity of lying down (sleeping), a 0.23 MET difference in the activity of sitting (watching TV), a 0.36 MET difference in the activity of stretching (yoga), and a 0.93 MET difference in the activity of light exercise (aerobics).

Based on these results, it could be concluded that the male had higher METs than the female. However, this result might be based on the fact that the male's BMI is generally higher than the female's. Since BMI has been studied as a significant parameter to affect a human's thermal sensation and comfort [39,40], the MET results were also compared in this study based on the BMI groups specified by the World Health Organization (WHO).

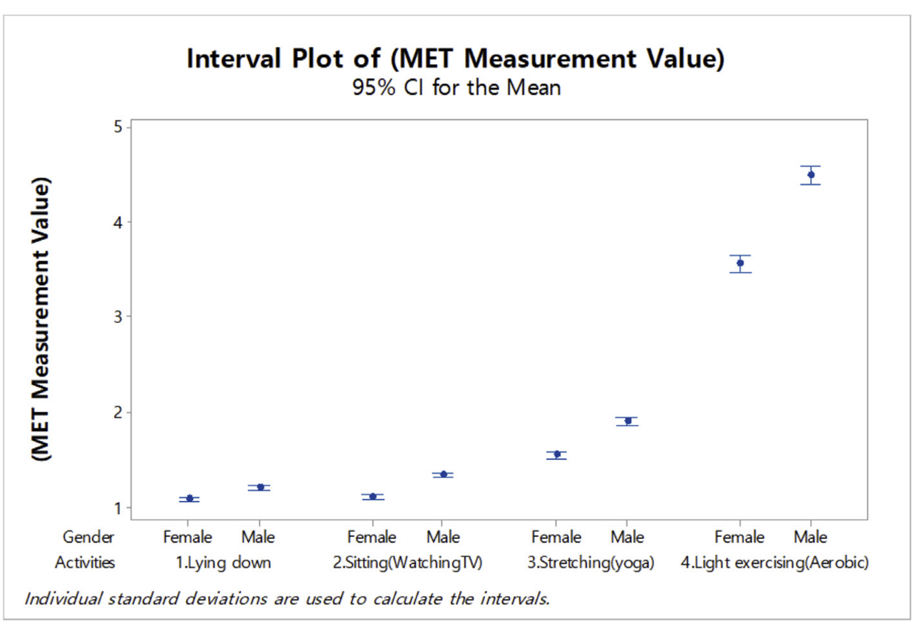


Fig. 5. Comparison of MET results by activity level and gender (all p-values < 0.001).

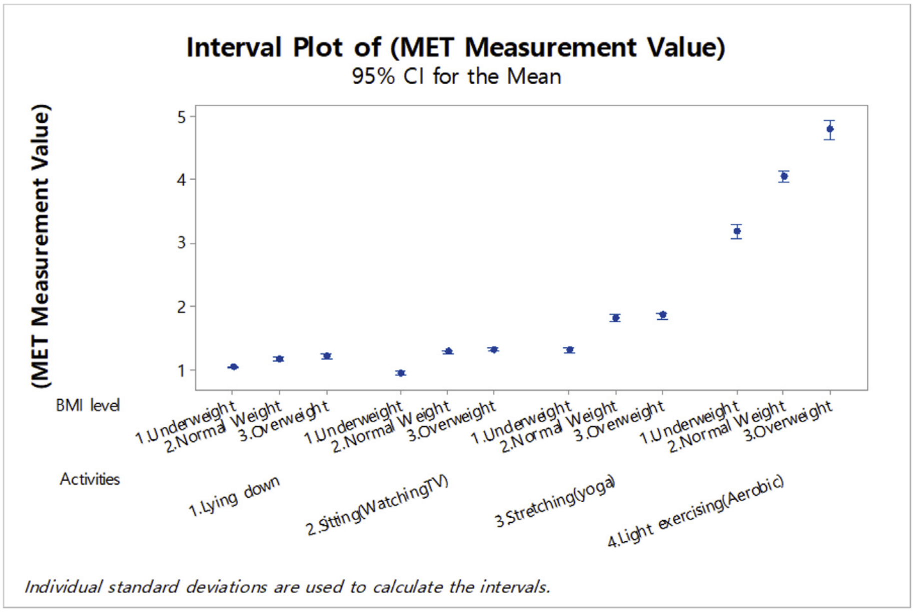


Fig. 6. Comparison of METs by BMI per activity level.

The WHO has classified BMI into four levels: underweight (< 18.5), normal weight (18.5–24.9), overweight (25–29.9), and obese (= > 30). In this study, the test participants were divided into three groups according to the WHO criteria: underweight (3 people), normal weight (14 people), and overweight (6 people). The male/female configuration can be found in Table 6. The results show that BMI is positively correlated with MET in all the selected activities level, as illustrated in Fig. 6. In the low-level activities from lying down (sleeping) to sitting (watching TV), the difference of METs between the BMI groups is statistically clear with a p-value of 0.001, but those rate differences are within 0.4 MET, which might be clear enough to confirm a significant difference in reality. However, the difference of METs between the BMI groups was much more significant in the high-level activities (especially in the light exercise, i.e., yoga) than that in the low-level activity. This finding indicates that the overweight group has a higher MET than the underweight even at the same exercise level.

Summing up the results (Figs. 5 and 6), the male MET is higher than the female MET. Overall, the male group has a higher BMI than female participants in this study. Fig. 6 illustrates the comparison results of measured MET levels between BMI per activity level based on the ANOVA. This analysis shows all the comparison sets are statistically significant with a p-value less than 0.001. Thus, BMI seems not to have a strong positive correlation with the MET values up to the activities levels 1 to 3 in illustrated in Fig. 6. Also, the MET values are relatively lower in the underweight group as compared to the normal and overweight groups, while the average MET values are highest in the normal weight group than the overweight. However, a proportional relationship was found between MET and BMI levels, especially at a high level of activity. i.e., Level 4 MET. As summarized in Table 9, the MET values increase, especially when BMI levels become higher.

3.2. Prediction of individual METs

As discussed in Methodologies, this study adopted the HRNet algorithm to predict the MET based on the use of the collected dataset from individual test participants. As discussed in section 2.5, 70% of the collected data from an individual were adopted as a training dataset, and 30% were used as a testing dataset. Therefore, all the prediction errors discussed in Fig. 7 were based on the individual prediction accuracy each test participant. Fig. 7 shows an error value difference between the predicted and actual values per activity level of 23 test participants (14 males, 9 females). As illustrated in Fig. 7, the error rates vary depending on individual test participants and also activity level adopted in this user study. This error is based on the difference between the estimated values by HRNet and the actual MET values. As the activity level increases, the error values also increase. Considering that the technical MET values of lying down position and light exercising are approximately 0.8 and 5.0, respectively, the error levels are relatively higher in the light exercising posture than in the lying down.

Fig. 8 summarizes the MET prediction accuracy level per activity. The MET error value increases from the low to the high MET level. This shows that the higher the MET is, the more difficult it is to make an accurate prediction. Regarding the accuracy rate, however, as shown in Table 10, the MET values for sitting (watching TV) and stretching (yoga) activities appear to be less accurate than that for light exercise (aerobics). Therefore, the analysis of prediction accuracy found:

- In the sitting (watching TV) activity, the MET prediction accuracy is very high (89%).
- In the case of stretching (yoga), it is easy to judge that it would result in a low MET because the movement is minimal. However, the real exercise intensity is high, and a high MET can be resulted. A MET prediction for the sitting (watching TV) and stretching (yoga) activities is less accurate than that for activities resulting in a high

Table 9
Mean METs by activity level and BMI level.

	(1) Lying down (sleeping)	(2) Sitting (watching TV)	(3) Stretching (yoga)	(4) Light exercise (aerobics)
1.Under weight	1.03 ± 0.14	0.94 ± 0.17	1.31 ± 0.27	3.19 ± 0.76
2.Normal Weight	1.16 ± 0.43	1.27 ± 0.45	1.82 ± 0.57	4.05 ± 1.19
3.Overwight	1.22 ± 0.45	1.32 ± 0.41	1.85 ± 0.50	4.80 ± 1.19

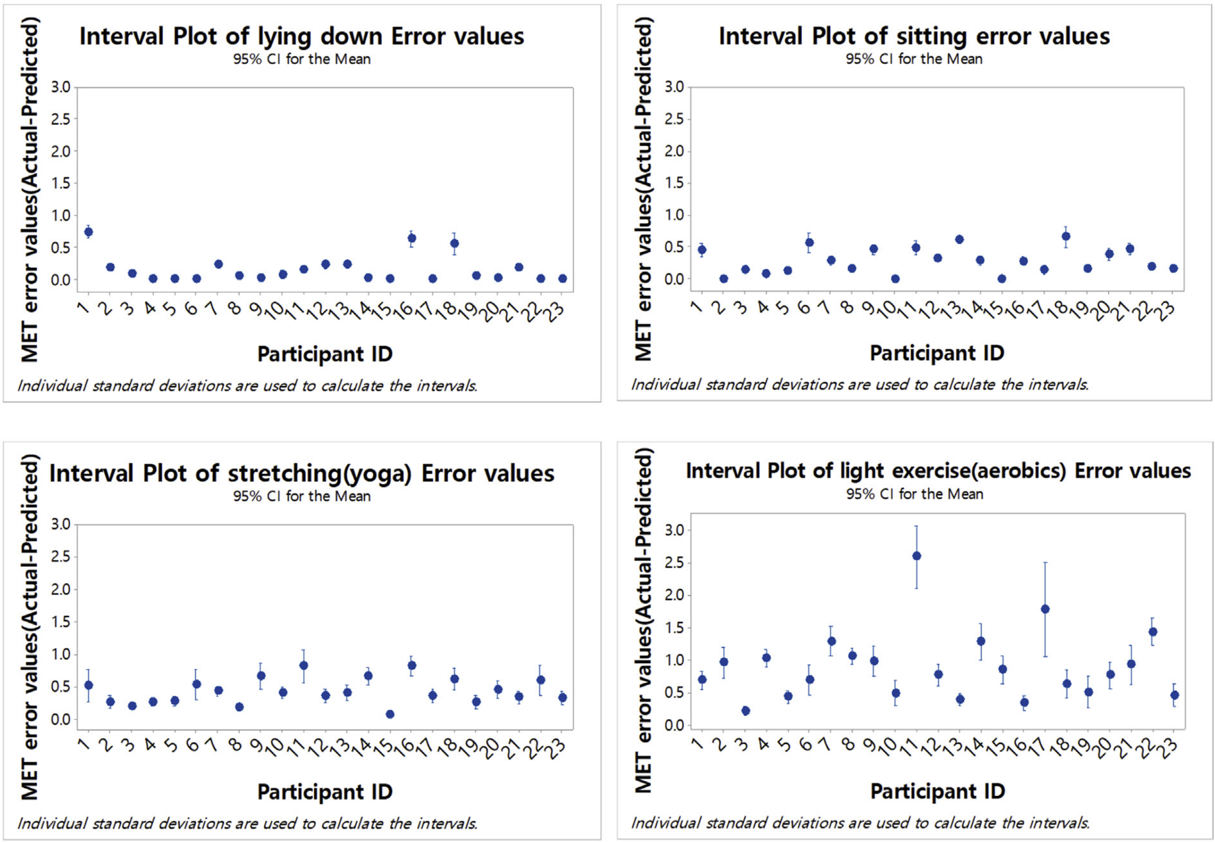


Fig. 7. Comparison of the prediction errors of individuals by activity level.

MET, such as light exercise (aerobics), but the difference is not significant. Table 10 summarizes the individual MET prediction results. The mean error value represents the actual MET minus predicted MET.

Based on the information of the individuals' MET prediction and its accuracy, discussed in Fig. 7, the accurate datasets were grouped by gender due to its significance to MET and thermal comfort levels. As illustrated in Fig. 9, the estimated accuracy of the males were lower than that of the females. Also, the error rate becomes increased when the activity level becomes higher, and the amount of the increased error rates were found very similar in each gender group while the absolute error levels were mostly higher in the males than in the females.

The MET error data were also grouped by BMI to find any significant pattern or relationship in this study, The overall error data values are distributed in Fig. 10 in each BMI range. When BMI becomes

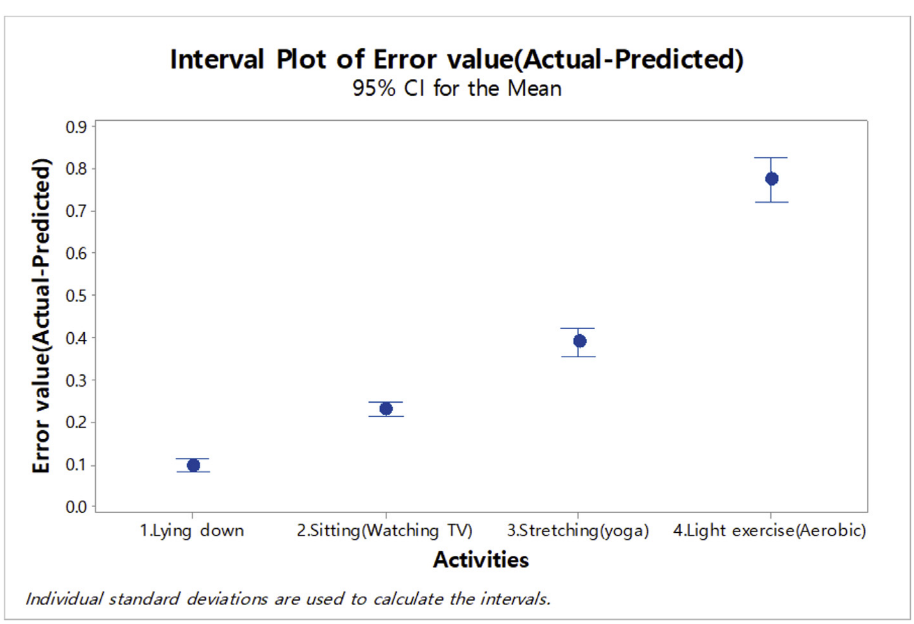


Fig. 8. Average Ranges of Error values according to the activity level.

Table 10
Summary of self-individual prediction results as an accuracy rate.

Total data	1. Lying down (sleeping)	2. Sitting (watching TV)	3. Stretching (yoga)	4. Light exercise (aerobics)
Mean MET	0.87 ± 0.15	1.29 ± 0.47	1.72 ± 0.55	4.53 ± 0.91
Mean error value	0.10 ± 0.20	0.23 ± 0.26	0.39 ± 0.32	0.78 ± 0.51
Accuracy rate	89%	82%	77%	83%

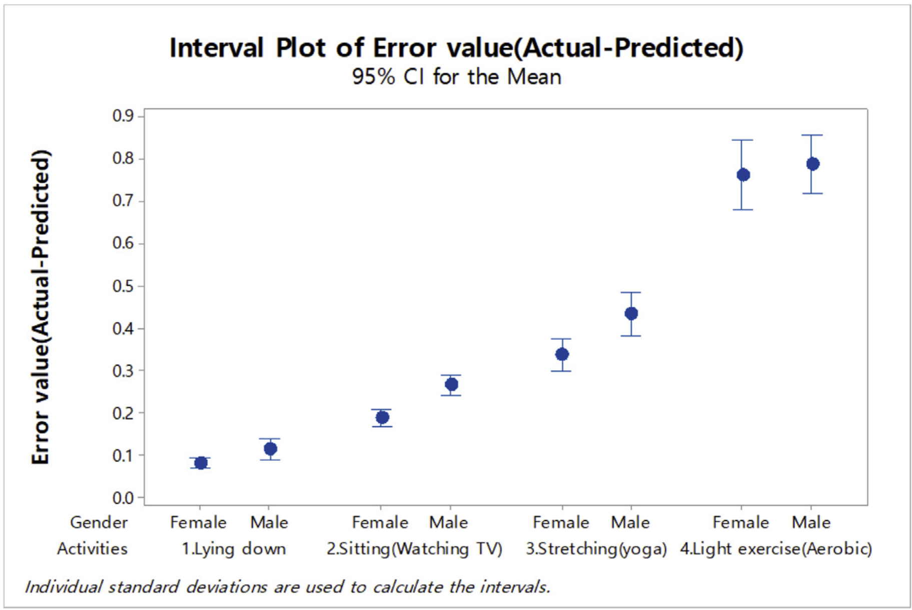


Fig. 9. Comparison of error value results by activity level and gender (Self-individual prediction).

higher, the average error rate also proportionally increased while the increasing rate also becomes larger in a higher activity level.

3.3. MET prediction using third-party data

In Section 3.2, all the tests for prediction were conducted per individual test participant based on his/her own training dataset. In this section, this study adopted a third-party MET prediction based on the use of the whole dataset collected from all the test participants except a selected test subject's, as a training dataset. In this method, 22 out of 23 test participants experimental data were used as training dataset while adopting the HRNet model, and the remained one human subject's data was used as a test dataset. In that way, the METs of 10 test participants were individually predicted. The 10 test participants were equally sampled from each gender group. The BMI groups were also equally considered for sampling the 10 participants.

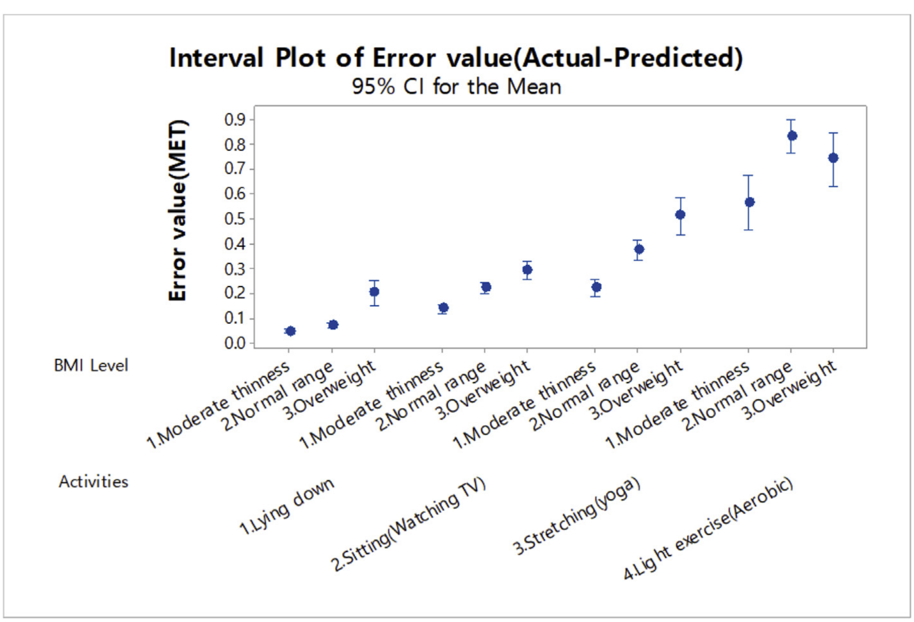


Fig. 10. Comparison of MET prediction error values according to the BMI by activity level (Self-individual prediction).

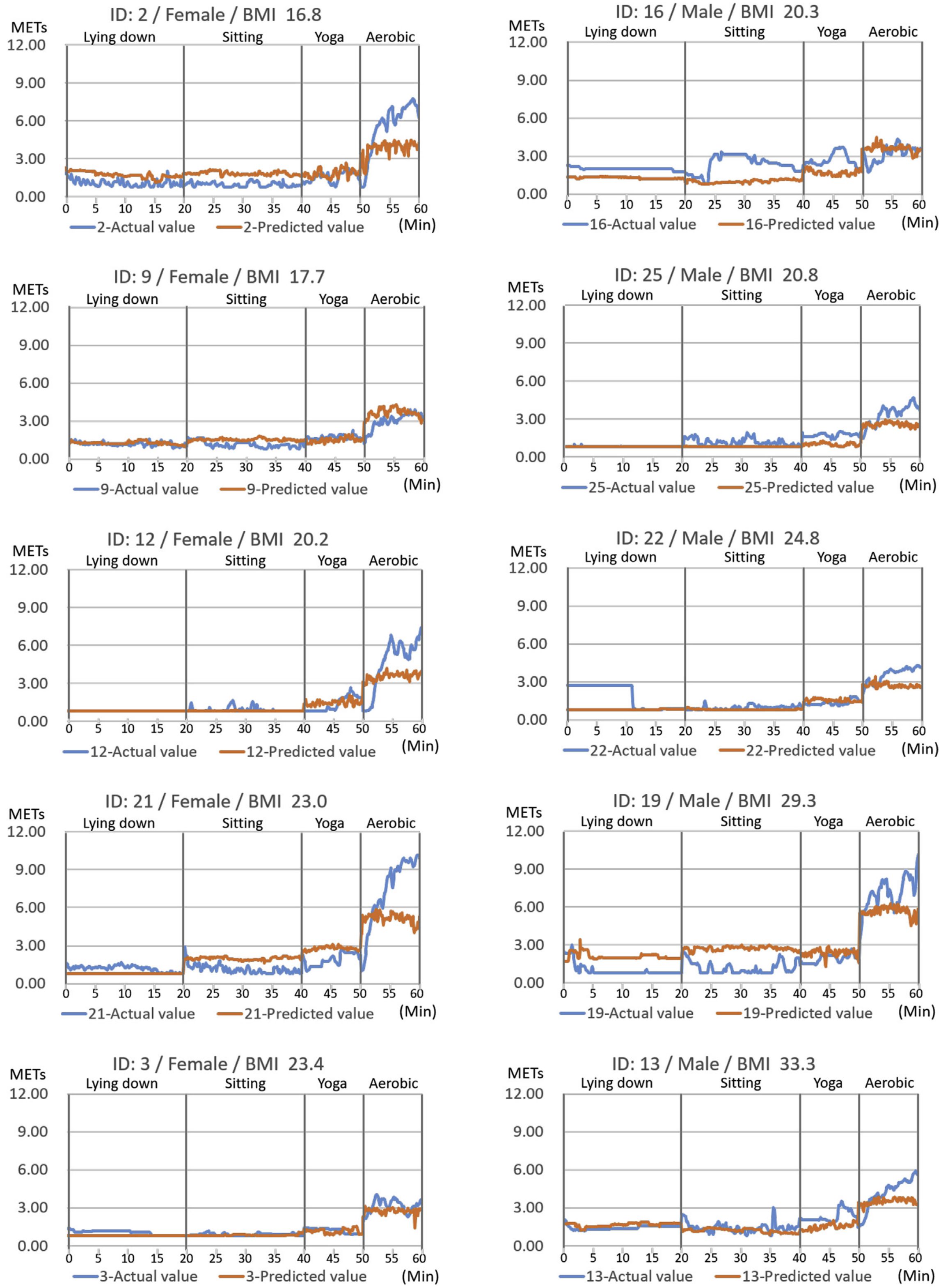


Fig. 11. Graph comparing the actual and predicted METs by gender and BMI.

Table 11
Comparison of Self MET prediction accuracy rate (%) and third-party MET prediction accuracy rate (%).

Activities	1.Lying down (Sleeping)	2. Sitting (Watching TV)	3.Stretching (Yoga)	4.Light exercise (Aerobic)	Total average
Self-MET prediction Accuracy rate(%)	89%	82%	77%	83%	**83%**
Third party MET prediction Accuracy rate(%)	68%	49%	70%	73%	**65%**

Overall, the third-party predictions appear to be much less accurate than an individual data based prediction, i.e., self-prediction, as shown in Fig. 11. The low-level activity (sitting (watching TV) and lying down (sleeping)) showed significant errors. In particular, with regard to the test participants (ID: 2,21,16,19), there were time ranges of prediction that show higher actual value than the estimated and vice versa. These inconsistent error patterns confirm that it is difficult to generalize the model established based on the 23 participants' dataset collected in this study, even in the low activity condition. In the case of the participants (ID: 2,12,19,21), there was a large difference between the actual and predicted values for the high-MET-level with light exercise (aerobics). The actual MET may be significantly different even though individuals perform the same exercise. Table 11 summarizes the results of third-party prediction accuracy rate and self-prediction accuracy rate. The average accuracy rates were 83% in the self-prediction and 65% in the third-party prediction, respectively. This result shows that it is difficult to generalize MET predictions based on the currently collected whole dataset. It may be because MET values are quite different depending on individual participants even though they generate the same activity. Therefore, for a general application in reality, the self-prediction modeling would be more robust compared to the third-party prediction.

Fig. 12 presents a prediction error rate by gender per activity level. At the lower-level activities, the male generally showed greater prediction errors than the female. The high-level activities, however, especially Level 4 (light exercise (aerobics)), showed larger prediction errors than the low-level activities. Therefore, it is difficult to judge the prediction accuracy level as a function of gender. This result also confirms that the prediction accuracy was lowered because the images taken at the low-level activities with minimal movements appeared large, especially for males. In the high-level activities, the actual METs of the females were high, but the movements looked smaller than those of the males; as such, the predicted MET was low.

Fig. 13 illustrates the MET prediction error values according to the activity and BMI levels. The BMI was divided into three levels: underweight, normal weight, and overweight. The magnitude of the prediction error seems to have no significant correlation with the BMI value. In detail, at Activity Levels 3 (stretching (yoga)), the higher the BMI was, the larger the MET prediction error appeared, but the difference was insignificant. Also, in case of Levels 1 (lying down (sleeping)), 2 (sitting (watching TV)) and 4 (light exercise (aerobics)), there is no consistent pattern found between BMI and MET prediction errors. Therefore, in the third-party prediction experiment, it can be concluded that there is no correlation of prediction accuracy between genders and BMI. Also, more learning time and more test sample sizes to obtain the desired level of prediction accuracy are required for an effective Deep Learning process, especially in the third-party prediction.

3.4. Comparisons with MET in comfort standards

The methodology of this study, which predicts the metabolic rate using heart rate, has shown considerable inaccuracies for the low heart rate range described in Section 2.1.2. Therefore, the results of measured MET are compared with those from existing references. Table 12 summarizes the following standards. (1) Current study: MET measurement data using the heart rate information of 10 subjects in the third-party prediction adopted in this experiment. (2) Zhai et al. [51]: Data obtained by measuring indirect calorimetry of 60 Chinese (Asian) college students. (3) ISO 8996 [25] and (4) ASHRAE 55 [52], which are frequently used as international MET standards. Because ISO 8996 and ASHRAE 55 are based on European and North American subjects, our experimental results are better compared with the experimental results of Zhai et al. when considering the Asian demographic.

In this comparison, a relatively significant error was noted in the low level activity for 1. Lying down (reclining): (existing references: 1.0, Zhai et al.: 0.8, ISO 8996: 0.8, and ASHRAE 55: 0.8). On the other hand, 2. Sitting (quiet, typing) was measured to be a very similar level to the other standards even in the low heart rate range. Unfortunately, there are no international standards available for 3. Stretching (yoga) and 4. Light exercise (aerobics) activities because such individual flexible activity conditions could not be established in the international standards that heavily rely on a pre-defined formula per distinct activity condition. However, ISO 8996 provides higher accuracy in higher MET (i.e., high activity level) prediction as a function of heart rate, adopted in current study, than the observation methods based on a look-up table per specific activity, which are introduced in other international standard methods, such as ASHRAE 55 and ISO 8896 (as summarized in Table 1).

Therefore, the method investigated in this research shows that a low metabolic activity (such as 1. Lying down) has a relatively lower accuracy rate for MET prediction than high metabolic activities. Considering that a primary activity condition of occupants in an indoor environment is around 1.0–1.2 MET (i.e., sitting condition), this study

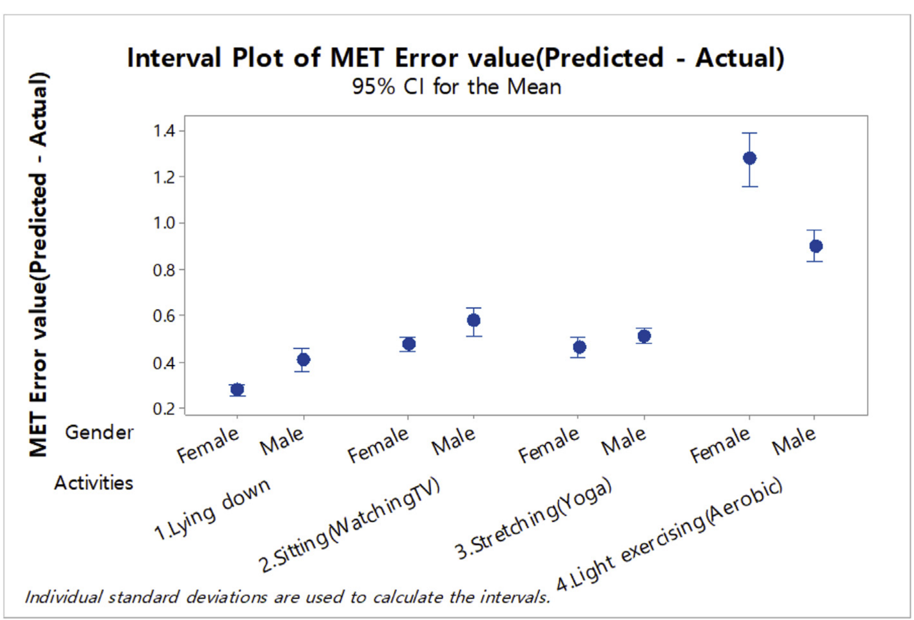


Fig. 12. Comparison of error value results by activity level and gender (third-party prediction).

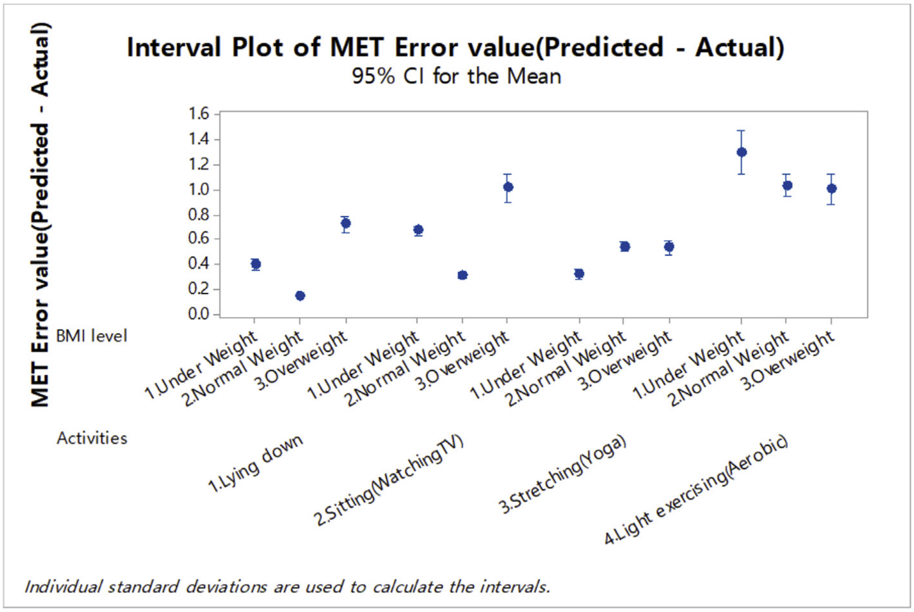


Fig. 13. Comparison of MET prediction error values according to the BMI by activity level (third-party prediction).

Table 12
Comparison of MET measurements between current study and standards.

Activities		Mean metabolic rate(SD)			
		(1) Current study	(2) Zhai et al., 2018 [51]	(3) ISO 8996 [25]	(4) ASHRAE 55 [52]
1. Lying down (reclining)	Male	1.0(0.3)[a]	0.8(0.2)	0.8	0.8
	Female	1.1(0.2)[a]	0.8(0.2)		
2. Sitting (quiet, typing)	Male	1.1(0.2)	0.9(0.2)	1.0–1.2	1.0–1.1
	Female	1.0(0.2)	0.9(0.2)		
3. Stretching (yoga)	Male	1.8(0.3)	–	–	–
	Female	1.5(0.4)	–	–	–
4.Light exercise (aerobics)	Male	3.9(1.3)	–	–	–
	Female	4.0(1.7)	–	–	–

[a] Significant differences between standards.

confirmed a potential contribution to building environmental comfort control as a function of estimated MET rate of an occupant in real time. However, additional research efforts should be made in a future study to enhance MET prediction accuracy, especially for low activity levels.

4. Conclusions

This paper presents a methodology for predicting the human MET for higher thermal comfort (TC). The existing MET prediction methods are expensive in resources and effort and require wearable devices [14,15]. To address such issues and to predict the MET in high accuracy, this study adopted the Deep Learning technology with the help of remote sensory devices, i.e., Kinect camera. The experiments involved four indoor activities (lying down (sleeping), sitting (watching TV), stretching (yoga), and light exercise (aerobics)) with different levels of intensity. The significant findings were investigated as follows:

(1) According to the gender and BMI-based analyses, the MET was higher in the males than in the females, and a higher BMI seems to affect a MET.
(2) After the learning of the individual MET, the accuracy of the MET self-prediction was relatively higher than the third-party prediction method.
(3) The third-party MET prediction was significantly lower in the prediction accuracy than the self-prediction approach.
(4) In the third-party MET prediction, there was no significant correlation between genders and BMI regarding a prediction error. In conclusion, more training data samples sizes for an effectively Deep Learning process are required to obtain a higher prediction accuracy.

Overall, the learning method using the Kinect camera is advantageous since it can reflect a unique individual behavior regardless of a behavior distinction or restriction. In this study, a series of human-subject experiments were conducted to construct training and testing datasets for four behaviors, respectively, and a fairly accurate prediction was achieved. This methodology can be applied for various purposes in multiple building typologies, especially for aged-care and healthcare facilities, where the occupants' environmental comfort is critical.

Most of the building HVAC systems are controlled based on room temperature and humidity conditions with a steady assumption about the occupants' Clo and MET based on the function of the Predicted Mean Vote (PMV) of the ASHRAE 55 [52], and those human factors are frequently not realistic as compared to the actual occupants' dynamic behavioral conditions. Since MET is difficult to measure with a simple sensor, it is generally treated roughly as a fixed default value [10,11] when calculating the PMV index. Therefore, the methodology investigated in this study using artificial intelligence enables the calculation of more accurate PMV values by reflecting the real-time MET. This research outcome allows better thermal comfort by enabling alterations to the operating temperature of the HVAC system based on the user-centered environmental control principle by accomplishing finely tuned thermal quality in real time.

Despite significant results, there are limitations affecting the outcome of this research. First, as test participants were recruited in a narrow age group, the generalization of the findings is made more difficult. Therefore, a future study should consider a wide range of demographic conditions for test participants, which would help increase the accuracy of the results and apply the findings across all population groups.

Second, due to the technical characteristics of the Kinect camera, the MET cannot be predicted when a corresponding activity is shown outside the camera's view angle. Last, there might be an inaccuracy in the heart rate measurement due to the subject's inconsistent emotional/

psychological status. Moreover, this prediction accuracy of this method becomes relatively lower in a lower metabolic condition, as compared to a higher condition. Nevertheless, this research is worthy of note as a new technology that enables better thermal comfort as a breakthrough method for conveniently evaluating individual METs indoors. For a further study, more efforts should be put on investigating how to promote the accuracy of MET estimation at a lower MET level by incorporating an advanced computational model, such as Artificial Intelligence algorithms. In addition, a larger number of training datasets should be collected to enhance the performance of the Deep Learning algorithm for more accurate MET prediction performance.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2019.106216.

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