Productivity prediction via human physiological signals for an optimum thermal environment

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Abstract. This study aims to understand the relationship between indoor temperature, physiological signals, thermal sensation, and productivity and to estimate the occupant's productivity. A series of human experiments were conducted with 48 participants, and local skin temperatures, heart rate, and thermal sensation data were collected in 6 temperature conditions. OSPAN (Operation Span Task) was used to measure the occupant's productivity and the LightGBM algorithm was used to generate a predictive model. The result verified that there is a significant correlation between certain local body skin temperatures and the occupant's productivity, and the overall thermal sensation between high and low performing groups was significantly different by gender and BMI groups. The result suggested gender, BMI, and two local skin temperatures as effective factors to predict the occupant's productivity.

Keywords. Thermal comfort, Productivity, OSPAN, Physiological signal, LightGBM
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1. Introduction

People spend most of their time indoors these days which were extended further due to the ongoing pandemic [1], and the indoor environment quality became more critical for the occupant's health and productivity in the buildings. Many studies demonstrated that the thermal environment has a strong impact on the occupant's emotions, behaviors, and productivity [2], and a comfortable indoor thermal environment showed a positive relationship with the occupant's given task [3,4].

Currently, predefined models, such as PMV, are used to control the thermal environment of the buildings. However, it doesn't consider individual occupant's characteristics and preferences, thus it has shown limitations to satisfy each occupant's preference and improve their productivity [5]. Considering thermal environment control, human physiological signal, such as local body skin temperature, heart rate, and EEG, has a significant impact on the occupant's thermal sensation [6] and it was also verified as an effective factor to predict the occupant's thermal sensation and comfort [7–9]. However, only a few studies dealt with the human physiological signals, thermal sensation, and the occupant's productivity under limited experiment conditions, thus further studies are required. Therefore, the purpose of this study is to investigate a relationship between indoor temperature, human physiological signals, thermal sensation, and productivity and to establish a productivity prediction model as a function of the occupant's physiological signals.

2. Methodology

2.1 Experiment equipment

The list of the sensors and their specifications are described in Table 1. A dry-bulb temperature and relative humidity were recorded by HOBO sensors, and a wire-type surface temperature sensor was used to measure the participant's skin temperature. A chest band type sensor was used to monitor the heart rate. The collected data was recorded on the laptop.

Tab. 1 – Specifications for data collection devices.

Device	Model	Specification
Dry bulb temp.	U12-012	Accuracy: ± 0.35°C (from 0 to 50°C, Resolution: 0.03°C
RH	U12-012	Accuracy: ± 2.5% (from 10 to 90%, Resolution: 0.05%)
Skin temp.	SBS-BTA	Accuracy: ± 0.5°C, Resolution: 0.03°C
HR	HER-BTA	Transmission frequency: 5kHz ±10%

2.2 Experiment room

The experiment room was located at Lawrence Technological University (LTU) in Michigan, USA. The size was 3 m (W) × 5 m (D) × 3 m (H) and there was one south-east facing window. The central HVAC system was disabled during the experiment, and the room temperature was controlled by the independent heating and cooling system with two nozzles. Each nozzle was placed at the opposite corner to prevent direct airflow to the participant, and a general office chair and desk were provided in the room (Figure 1). The Venetian blind covered the window to minimize the impact of the daylight.

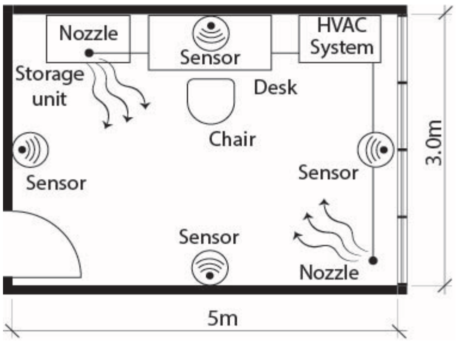

Fig. 1 – Experiment room plan.

2.3 Productivity test

Operation Span Task (OSPAN) was used to measure the participant's working memory capacity as a productivity measurement. Working memory supports temporary storage and manipulation of the information for comprehensive cognitive tasks in daily works [10], which is critical to understanding productivity. In the OSPAN, the participant needs to answer a simple math question by selecting 'Yes' or 'No' (e.g. 1+1=3, Yes or No?) and then needs to read and memorize a random letter (e.g. A or T). After a random series of math questions and letters (Maximum 6), the participant needs to select the letter (s) in chronological order. This set was repeated 20 times.

2.4 Experiment procedure

A series of human experiments were conducted that was approved by the Institutional Review Board at LTU (IRB #01418). Every participant was asked to wear basic clothes (Clo level 0.55 or 0.59; Long-sleeve tee or shirts, long pants, socks, underwear, bra). The participant was assigned to 6 experiment conditions randomly (18°C, 20°C, 22°C, 24°C, 26°C, and 28°C). The temperature was controlled the same during the experiment, and every data was recorded every minute.

Once arrived, the participant waited 20 minutes in the designated area to neutralize their physical status, while taking the survey and signing the IRB consent form. Once entered the room, the participant sat on the chair and attached the required sensors to their body spots. This study used a total of 8 local body spots (Forehead, neck, chest, arm, wrist (in), wrist (back), and belly) and heart rate as a physiological signal. When they were ready, the participant took the first survey about overall thermal sensation. The Likert 7-point scale question from the ASHRAE PMV was used (Table 2). Then, the participant took the OSPAN task and one more thermal sensation survey.

Tab. 2 – Thermal sensation questionnaire

-3	-2	-1	0	1	2	3
Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot

2.5 Data analysis and predictive model

The collected data were analysed by multiple statistical methods, including T-test, correlation analysis, etc. Minitab and Microsoft Excel were used as initial analysis tools. Based on the analysis, LightGBM (Light Gradient Boosting Machine) was used to generate a predictive model. LightGBM is an improved version of the GBM model which was designed for faster training speed and high efficiency, accuracy, and to support GPU learning [11]. The boosting algorithm is an ensemble method that combines several sequential models to improve the performance of prediction or classification. The gradient boosting method is one way to adapt boosting algorithm that focuses on the important weights. LightGBM algorithm is a gradient boosting framework that uses leaf-wise tree growth algorithms. This study adapted the LightGBM classifier model to predict OSPAN performance as a function of the participants' physiological signals. The proposed model was trained in Python 3.8, TensorFlow-2.5.0 environment, and two Intel Zeon Silver 4215R CPUs, Nvidia GeForce 3090, 128G RAM Workstation were used.

3. Results and discussions

3.1 Physiological signals and thermal environment

50 participants' data were collected and 48 datasets were analysed due to the recording errors. Demographic information including age, height, and weight was surveyed and no one reported a specific health issue. Most of the participants were students in their 20s (Avg. age: 23.1). Figure 2 and 3

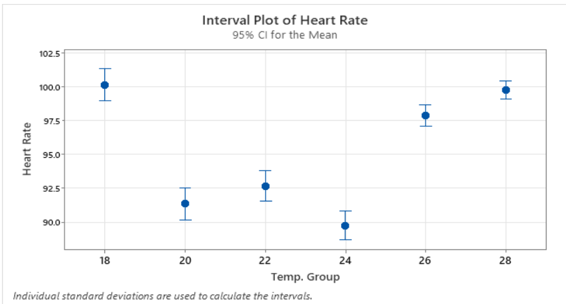

Fig. 2 – Interval plot of heart rate by the temp. group.

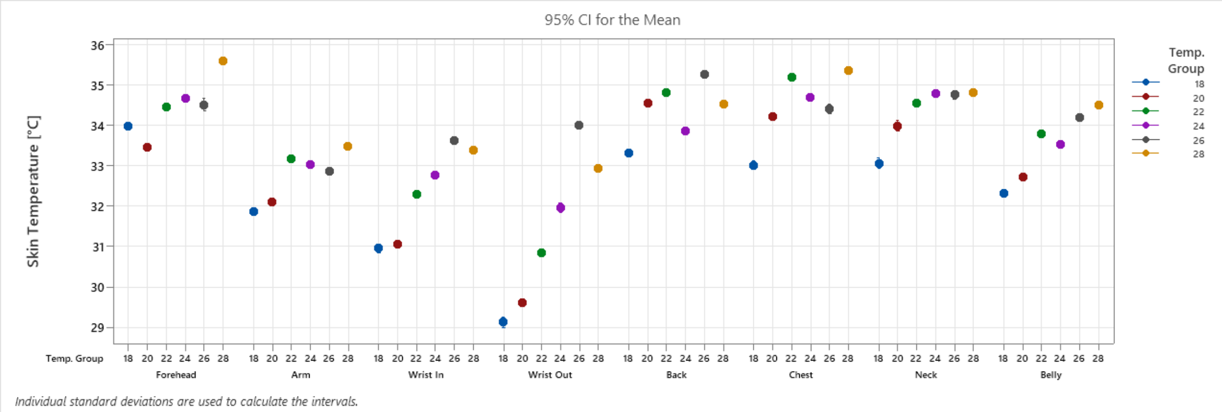

Fig. 3 – Interval plot of local body skin temperature by the temperature group.

demonstrate the interval plot of local skin temperature and heart rate by the temperature group. It shows that local body skin temperatures and heart rate increased as the indoor temperature increased mostly. The correlation analysis showed (Table 3) that all physiological signals were correlated with the indoor temperature positively ($p<0.001$). Wrist (Out) and wrist (In) showed a relatively strong correlation than the others, while heart rate showed an insignificant correlation, due to relatively high heart rate in the temp. group 18.

Tab. 3 – Correlation between temperature groups and physiological signals.

Fore head	Arm	Wrist (in)	Wrist (Out)	Heart rate
0.333	0.399	0.539	0.590	0.04
Back	Chest	Neck	Belly	
0.227	0.309	0.255	0.425	

The correlation analysis between overall thermal sensation (OTS) and physiological signals is shown in Table 4. Although it does not demonstrate general tendency, wrist (In) and wrist (Out) showed a significantly positive correlation with the OTS, demonstrating potential as an effective factor to predict thermal sensation and productivity.

Tab. 4 – Correlation between OTS groups and physiological signals.

Fore head	Arm	Wrist (in)	Wrist (Out)	Heart rate
-0.016	0.266	0.476	0.544	-0.029
Back	Chest	Neck	Belly	
0.043	0.166	-0.094	0.115	

3.2 OSPAN result

The average of the OSPAN appeared 88.5 out of 100, ranging from 55 to 100. Figure 4 demonstrates that the score is higher when the temperature is

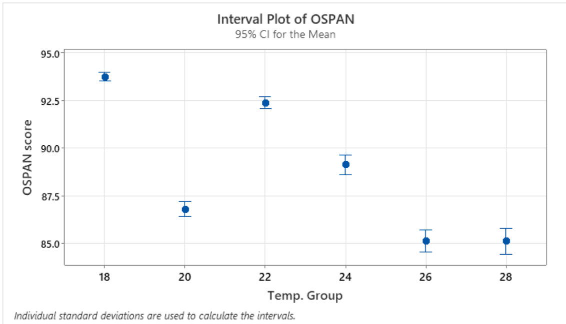

Fig. 4 – Interval plot of OSPAN score by the temperature group.

relatively low, and the correlation results verified its negative relationship (Pearson R: -0.225, $P < 0.001$). The relationship between OSPAN and OTS appeared similar which demonstrates that indoor temperature and thermal sensation are negatively correlated with the occupant's productivity.

Considering thermal comfort in the built environment, gender and BMI have a significant impact on the occupant's thermal sensation. Figure 5 shows the OSPAN score by the OTS and gender group. Both male and female groups showed higher performance when their OTS was lower, and both groups' correlations appeared negative (Pearson R – Female: -0.207, Male: -0.278).

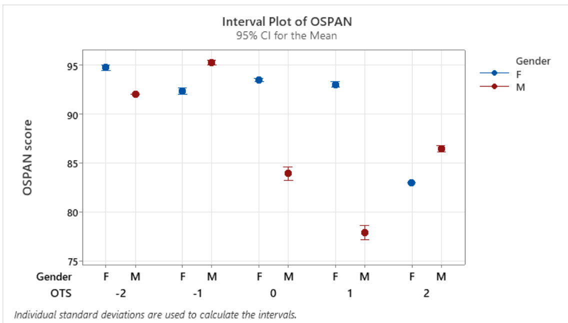

Fig. 5 – Interval plot of OSPAN score by the OTS and Gender group.

Figure 6 demonstrates the OSPAN score by the OTS and BMI groups. Both groups showed higher scores when the participants felt cool or slightly cool, and both groups' OTS were negatively correlated with the OSPAN score (Group 1: -0.269, Group 2: -0.395).

Considering the analysis result, it is clear that some human physiological signals are correlated with the occupants' thermal perception. Also, both gender and BMI affect occupant's thermal sensation, which has a significant impact on their performance on the given tasks. This demonstrates the potential of the human physiological signal as a factor to predict the occupant's thermal comfort and productivity.

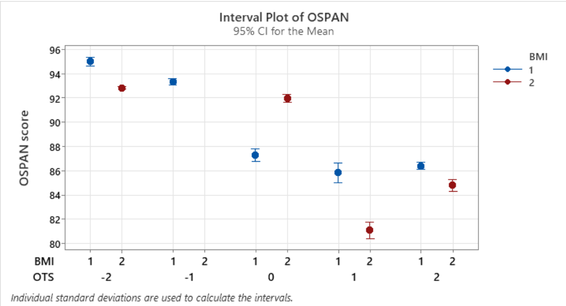

Fig. 6 – Interval plot of OSPAN score by the OTS and BMI group (1: Healthy or underweight, 2: Overweight or beyond).

3.3 Predictive model

Based on the analysis, selective datasets were used to generate a predictive model for the occupant's productivity as a function of human physiological signals. Original datasets included gender, BMI, local body skin temperatures, and heart rate as well as thermal sensation survey results. Considering that the wrist showed a relatively high correlation, as well as the practicality of the monitoring system (smartwatch and thermographic camera), wrist (Out), forehead, and heart rate was selected as input components. Also, the OSPAN score was divided into two groups, high and low performing groups, based on the average score.

Table 5 shows the components of each dataset for the LightGBM classifier. Gender and BMI were the default component in each dataset, and the other components were randomly assigned. Total 7 datasets were generated and tested to compare the predictive performance for high-performing and low-performing groups. The number of rows in the dataset was 10,075, and the number of each OSPAN group was 7,219 (High-performing) and 2,856 (Low-performing) respectively. The data was split into the training set (66%) and the test set (33%). The number of the rows in the training set's OSPAN group was 4,835 (High-performing) and 1,915 (Low-performing), and the number of the rows in the test set's OSPAN group was 2,384 (High-performing) and 941 (Low-performing) respectively.

Tab. 5 – Dataset component.

Dataset	Component	Target
Data 1	Gender, BMI, Wrist (Out)	
Data 2	Gender, BMI, Forehead	
Data 3	Gender, BMI, Heart rate	
Data 4	Gender, BMI, Wrist (Out), Forehead	OSPAN High / Low
Data 5	Gender, BMI, Wrist (Out), Heart rate	
Data 6	Gender, BMI, Forehead, Heart rate	
Data 7	Gender, BMI, Wrist (Out), Forehead, Heart rate	

Tab. 6 – Trained model accuracy.

Dataset	Accuracy (%)	Dataset	Accuracy (%)
Data 1	92.87	Data 5	95.30
Data 2	93.17	Data 6	97.14
Data 3	81.2	Data 7	99.63
Data 4	99.48		

Each dataset was used to train each model using the LightGBM algorithm. Table 6 shows the accuracy of each trained model. Overall models demonstrated relatively high predictive performance over 91% accuracy, except the model that the data 3 was used. The heart rate showed the lowest correlation to the OSPAN score in the prior analysis, thus, the accuracy appeared relatively lower than the others (81.2%). When every component was used, the accuracy was the highest at 99.63% respectively and for one component, data 2 demonstrated the highest accuracy at 93.17% respectively, among data 1 - 3. This result verifies that there is a significant relationship between certain human physiological signals and the occupant's productivity, and its

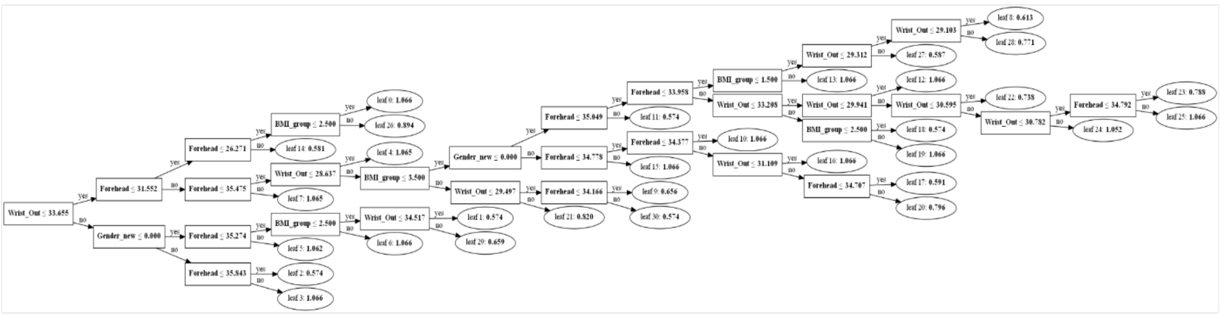

Fig. 7 – Decision tree of the dataset 4.

potential as a control factor for building's thermal environment. Considering the practicality of using a thermographic camera and smartwatch, data 4 showed the highest accuracy at 99.48% which is similar to the one from data 7. Figure 7 indicates the generated decision tree model based on dataset 4. This decision tree can be applied to the smart indoor temperature control system which can predict the occupant's productivity and provide a personalized thermal environment for the occupant's high productivity.

4. Conclusions

This study aimed to understand the relationship between indoor temperature, human physiological signals, thermal sensation, and productivity and to develop a productivity prediction model as a function of the occupant's physiological signals.

The result verified that there is a negative correlation between certain local body skin temperatures and the occupant's productivity, and the overall thermal sensation between high and low performing groups was significantly different by gender and BMI groups. The result suggested gender, BMI, and two local skin temperatures, wrist (out) and forehead, as effective factors to predict the occupant's productivity by using the LightGBM algorithm. The findings of this study can be implemented in the smart thermal environment control system to provide optimum temperature conditions for the occupants' high productivity.

As a future study, various participant groups with larger sample sizes are required for other human factors, such as age and race, to increase the validity and accuracy of the results. Also, subjective factors, such as personal thermal preferences, cultural preferences, may affect thermal perception and productivity, so these factors should be studied in the future.

5. Acknowledgement

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7. Data Access Statement

The datasets analysed during the current study are not available because the extended studies are currently ongoing but the authors will make every reasonable effort to publish them in near future.