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Effects of the indoor environment on EEG and thermal comfort assessment in males

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ABSTRACT

This study investigated the effect of indoor thermal conditions on electroencephalogram (EEG) signals and used logistic regression to discriminate indoor, thermal comfort. Twenty male subjects were recruited to record resting EEG signals under thermal conditions consisting of a combination of temperature, relative humidity, and air velocity. Subjective questionnaires were used to collect individuals' perceptions of the environment and as classification criteria for developing logistic regression models. The results indicated that at 22 °C and 25 °C, θ, β1, β2, and γ waves were highly similar, and velocity was also highly similar for all EEG waves at 0.5 and 1 m/s. For β1, β2, and γ, 70% RH can be used as the high humidity cut-off point in the humidity test. In addition, regression models for indoor comfort discrimination utilizing the frequency bands relevant to comfort are regressed, and the total model revealed that 88.6% of the data were correctly categorized. This research serves as a starting point for further research into the coupled environment and neuronal mechanisms.

1. Introduction

The quality of the indoor environment is strongly tied to the efficiency of work and study, and it is intimately linked to the mental and physical health of people [1]. Wasted energy will be generated when the indoor environment is not effectively regulated. As a result, indoor thermal comfort has received much attention in recent years. Thermal comfort is essentially a nervous system activity that is dependent on human, subjective sensations. Due to wearable devices [2], objective, physiological techniques are being used to assess people's feelings in thermal environments, such as skin-temperature detection [3], thermal-image recognition [4], heart rate, and electroencephalogram (EEG) readings [5]. Among them, EEG has been widely used by researchers to conduct emotional evaluations and fatigue-driving studies [6,7]. In assessing indoor environments, some researchers have employed EEG measurements to explore the impact of changes in acoustic, thermal, and olfactory variables [8–10]. Although many studies have been carried out on thermal comfort, few studies have used EEG features to distinguish between different thermal comfort states.

Fanger. P. O proposed the predicted mean vote (PMV) index in 1950 by combining the heat dissipation and heat production equations associated with the human body and the predicted percentage dissatisfaction (PPD) index by predicting the mean response of a large population based on the ASHRAE heat sensation scale. The resulting PMV-PPD model is the most representative model proposed by Fanger based on the principle of human thermal balance and has long been widely used to assess indoor, thermal comfort [11,12]. The ambient environment and personal factors are the two key parts of the model. However, the human thermal experience and the individual's ability to respond to the thermal environment were ignored in the design of the PMV model, which does not match the actual thermal sensation [13–15]. As a result, Fanger proposed that the actual thermal sensations of people in nonair-conditioned environments in the tropics may be overestimated due to reduced expectations of the thermal environment, and the introduction of a psychological expectation factor "e" to modify the PMV model, called the extended PMV model (ePMV), was used for nonair-conditioned spaces in warm and humid climates [13]. The adaptive PMV model (aPMV) integrates the influence of cultural, climatic, social, psychological, and behavioural factors on the perception of indoor, thermal comfort and is an example of a naturally-ventilated built environment [14]. To compensate for the discrepancy between the PMV and the thermal perception of people in buildings, Humphreys et al. [16] proposed a new predictive mean voting (nPMV) model to balance the variations in PMV and temperature perception. However, although these methods are correct architecturally, they fail to directly relate to the individual.

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The human nervous system and the brain coordinate the movement of the entire body through signals transmitted by neurons. The brain, as the core of the nervous system, is the focus of neuroscience research and is closely related to the body's perceptual feedback. EEG is an effective means of identifying human comfort models by measuring electrical signals on the surface of the scalp and recording the spontaneous and rhythmic electrical activity of groups of brain cells [17]. According to the frequency of EEG signals, they can be classified from low to high into δ waves, 0.5–4 Hz; θ waves, 4–8 Hz; α waves, 8–13 Hz; β waves, 13–30 Hz; and γ waves, 30 Hz or higher. δ waves (0.5–4 Hz) appear mainly during sleep or slow-wave sleep; θ waves (4–8 Hz) appear during states of drowsiness or emotional distress; α waves (8–13 Hz) appear when eyes are closed and relaxed awake; β waves appear during mental activity and arousal; and γ waves appear during sensation and the binding of different neurons [18]. In the past, EEG was used in medicine to identify different mental states, and it was considered one of the tools to discern emotional responses [19]. Thus, EEG signals can be utilized to assess a person's state in a given environment. Present studies have observed changes in brain wave characteristics by changing the indoor environment. Wu, Meng, and colleagues [20] found that an increase in δ waves implies that participants are more likely to be sleepy, whereas a decrease in β waves indicates that subjects have lower levels of concentration or alertness in hot conditions. Son et al. applied EEG in experiments with temperature steps to obtain thermal pleasure and increased frontal midline Fz relative θ frequency but lowered frontal, central, and parietal midline relative β power with no significant effect on α and γ [21]. Wang et al. presented a mental workload by frontal θ and parietal α power in their temperature experiment [22]. Humidity and temperature variables have been measured together in prior experiments. Zhu et al. recorded EEG signals and cognitive tests under different temperature and humidity conditions [23]. The results showed that in a high-humidity environment, the relative power of the δ-band increased with increasing temperature, but the relative power of the θ, α, and β-bands appeared to decrease significantly. In another study [24], three occipital lobe channels (P7, O1, and O2) corresponded to thermal comfort under variations in temperature and humidity. However, few studies have examined how airflow affects thermal comfort. An experiment on EEG perception of airflow was revealed by a researcher [25] who noted a clear difference in amplitude between β and γ under the influence of airflow.

The aforementioned studies have described the characteristic changes in EEG readings under different thermal environments, such as the frequency band energy ratio and channel discrepancies attributable to the environment. Nevertheless, it is unclear whether the features of EEG signals can be employed to identify the specific environment. There are also few studies using EEG signals to develop thermal comfort discrimination models.

The objective of this study was to test the similarities and differences among the characteristics of EEG signals in different environments of temperature, humidity, and velocity. Therefore, partial channels were chosen to verify the differences in EEG signals in different environments using the statistical results of a two-factor ANOVA. Second, correlation analysis was used to draw correlations between EEG signals in various environments with absolute power spectra involved in developing a regression model for comfort discrimination based on EEG waves. This study also determines the level of comfort in the indoor environment that aids in improving the thermal comfort of the occupants; it will further facilitate the atmosphere and conserve energy in the building when paired with heating, ventilation, and air conditioning (HVAC).

2. Test apparatus and methodology

2.1. Experiment

The experiment was designed to investigate the association between EEG signals and thermal comfort levels and was executed in diverse, interior conditions with a focus on the changes in brain waves in humans at rest. To reduce noise and industrial frequency interference to the greatest extent possible, the faculty office was chosen as the measuring location for the resting state EEG recordings.

The trial took place in the spring of 2021, from March to April. The climatic laboratory dimensions were 3 m × 4 m x 2.8 m on the Guangzhou campus of Sun Yat-sen University (Fig. 1). Subjects conducted 7 sets of 5-min tests in the climate lab on a combination of temperature, relative humidity, and air velocity for the analysis of EEG amplitude under changes in the interior environment.

To ensure that the indoor environment in the climate laboratory was homogeneous, additional tests with environmental measurements were performed. Participants and equipment were measured at four corner points and subject locations in the climate laboratory, and the results obtained are shown in Table 1.

2.2. Subjects

The sample size for this experiment was designed based on logistic regression (Gpower software) with the main, design parameters of $\alpha = 0.05$ and $1\text{-}\beta = 0.8$, and a medium-effect size (0.5), resulting in a sample size of 17 participants [26–28]. To reduce the effects of gender, age, and weight, the experiences and social backgrounds of school students were considered and deemed similar. A total of twenty healthy male students with a college degree or higher (age: 21 ± 2 years; body mass index: 22.9 ± 0.8 kg/m^2) were randomly recruited for the experiment. All of the participants were in good health and did not engage in any addictive behaviours. Myopic participants were obliged to wear frame glasses instead of contact lenses.

Prior to the experiment, participants had to keep their heads clean to reduce the impedance between the test electrodes and the scalp. Participants were asked to get enough sleep the night before, eat a healthy diet, not consume alcohol for 12 h, not smoke for 8 h, and avoid stimulating beverages such as coffee and energy drinks.

During the experiments, the subjects were uniformly outfitted in shirts, slacks, and sneakers to keep their clothing's thermal resistance at 0.7 clo, and they were asked to sit peacefully in a chair in a relaxed position with a basal metabolic rate of 1.0 met during the test. In addition, each subject underwent EEG in various environmental conditions, and they were requested to fill out a thermal comfort questionnaire as a subjective measurement following each set of cases.

2.3. Equipment

The experimental indoor temperature was controlled by using a household air conditioner and an electric oil heater. The humidity level in the laboratory was controlled by using a dehumidifier and an air purifier humidifier. A thermal anemometer was used to measure the room temperature and wind speeds, while a Seiko GSP-6 humidity logger was used to detect the relative humidity. For recording the EEG data, subjects were required to wear EEGO's 64-channel EEG headgear. All instrumental accuracies and specifications are provided in Table 2 and Table 3.

2.4. Experimental conditions

Since the experiment was performed in Guangzhou in the spring, the climate laboratory had to simulate a variety of indoor environments as follows: three levels of temperature (22, 25, and 28 °C), three levels of relative humidity (60, 70, and 85%), and three levels of airflow (0, 0.5, and 1 m/s). The environmental parameters were designed as follows.

Given that the ambient temperature indoors is usually controlled in the comfort range according to the PMV model [29], 26% of people are dissatisfied with their surroundings when the PMV is ±1. Therefore, the temperature range chosen for this experiment ranged from slightly cool (PMV = −1, 22 °C) to neutral (PMV = 0, 25 °C) to slightly hot (PMV = 1,

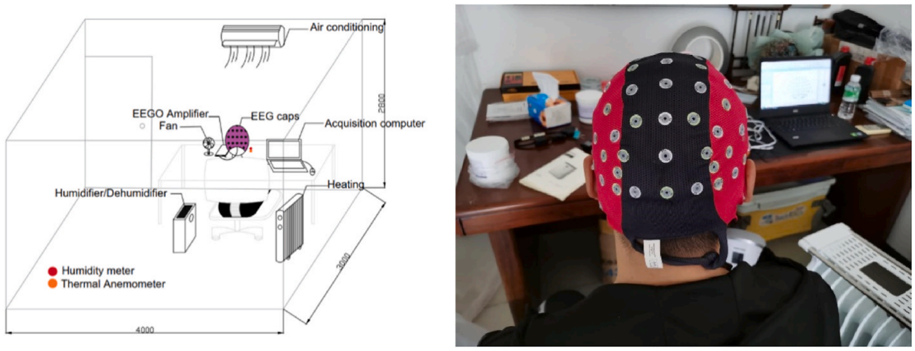

Fig. 1. Experimental environment.

Table 1
Environmental parameters.

Group	Setting point	Air temperature	Relative Humidity	Airflow rate
1	22 °C, 60% RH, 0 m/s	21.9 ± 0.2 °C	57.5 ± 0.5% RH	0.1 ± 0.1 m/s
2	22 °C, 70% RH, 0 m/s	22.0 ± 0.1 °C	69.3 ± 0.8% RH	0.0 ± 0.0 m/s
3	22 °C, 85% RH, 0 m/s	22.0 ± 0.0 °C	84.5 ± 1.1% RH	0.0 ± 0.0 m/s
4	25 °C, 60% RH, 0.5 m/s	24.8 ± 0.1 °C	62.8 ± 1.1% RH	0.5 ± 0.0 m/s
5	25 °C, 60% RH, 1 m/s	25.0 ± 0.3 °C	61.0 ± 0.7% RH	1.1 ± 0.1 m/s
6	25 °C, 60% RH, 0 m/s	25.1 ± 0.1 °C	58.8 ± 0.8% RH	0.0 ± 0.0 m/s
7	28 °C, 60% RH, 0 m/s	27.9 ± 0.2 °C	58.8 ± 0.8% RH	0.0 ± 0.0 m/s

Table 2
Instruments for environment parameters measurement.

Parameter	Instrument	Range	Accuracy
Air temperature	FLUKE F923	0–45 °C	±0.5 °C
Airflow	FLUKE F923	0.2–20 m/s	±0.01 m/s
Relative humidity	GSP-6	5–100%	±3%
Dehumidifier	GREE DH40EF	–	–
Humidifier	Philips AC2726/00	–	–
Heating	GREE NDY19-X6021	–	–
Electroencephalograph	ANT neuro inspiring technology	–	–

Table 3
Detail of the EEG recording device.

Device	Detail
Waveguard cap	Frontal lobe (Fp1, Fp2, Fpz, Fcz, Fz, AF3, AF4, F1–F8, FC1-FC4, AF7,AF8)
	Temporal lobe (FT7, FT8, FC5, FC6, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P5–P8)
	Parietal lobe (C1–C4, CZ, CP1-CP4, CPz, P1–P4, PZ)
	Occipital lobe (PO3-PO8, POz, O1, O2, Oz)
	Bilateral mastoid electrode (M1 M2)
	Grounding electrodes (GND)
64-EEGO Amplifier	sampling frequency: 1000Hz
	Impedances: below 5 kΩ

28 °C) [10,30].

The humidities were selected at three levels (60%, 70%, and 85% RH) at 22 °C. Humidity essentially has no effect on human comfort when temperature, wind speed, and radiation temperature are all within tolerable ranges [31]. According to a study conducted in Chongqing [32], residents living in areas with different humidity scores were relatively stable for 20–60% RH when the temperature was at 25 °C and 28 °C. However, when the humidity exceeded 70% RH, people's perceptions of humidity increased significantly.

The indoor airflow rates were set at three levels of 0 m/s, 0.5 m/s, and 1 m/s to follow previous research on air velocity [25,33].

The formal procedure of the experiment was conducted for a total of approximately 200 min with one subject participating in each session. At the moment t0 the subject entered the faculty office to prepare, the EEG cap was placed on his head. The conditions in the room were 26 °C and 65% RH. After waiting for the conditions to stabilize, the subject entered the climate room and sat for 5 min to acclimate to the environment, followed by a 5 min EEG recording. Finally, the subject was asked to complete the subjective questionnaire. After that, the subject was asked to leave the climate chamber, and then the environment was changed. The new environment was stabilized before the subject was asked to readapt for 5 min to complete the EEG recordings and the subjective questionnaire. Ultimately, each subject had to complete 7 groups of experiments, and the experimental procedure is shown in Fig. 2. For each adaptation time, recording EEG time and subjective evaluation time, the procedure was the same.

2.5. Subjective thermal comfort

Before each EEG recording, a questionnaire was provided to collect subjective responses to assess the thermal state of the room (Fig. 3). Considering the different environmental preferences of the subjects, thermal comfort and sensation were evaluated on a continuous, 5-point scale indicating the satisfaction of the participants.

2.6. Data recording and analysis

Brain activity was recorded by placing a 64 EEG headset (ANT neuro inspiring technology, Inc., Netherlands) on the scalp. The 63 electrodes consisted of the frontal lobe (21 channels), temporal lobe (16 channels), parietal lobe (14 channels), and occipital lobe (10 channels), and reference electrodes (2 channels) were placed on the mastoids. The ground electrode was placed on the GND, while the reference electrodes were placed on the CPZ. The sampling frequency was 1000 Hz (Table 3).

Advanced Source Analysis (ASA) is a highly-flexible EEG/ERP and MEG analytical package with a variety of source reconstruction, signal analysis, and MRI-processing features. It was developed by ANT Neuro inspiring Technology, Inc., for EEG data preprocessing. The data were first previewed, and the useless channel (EOG) was removed. Some signal channels with large fluctuations, such as spikes and excursions in the EEG channels, were excluded from the analysis. All EEG signals were visually inspected, and channels with persistent artefacts were removed. Only three channel was removed from the analysis out of all subjects' data, and finally, a total of twenty subjects' EOG channels were excluded [34,35]. Since the objective of this study was to investigate how human

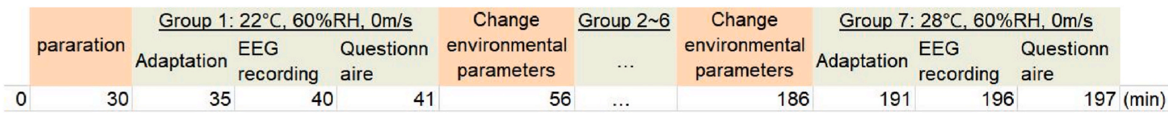

Fig. 2. Experimental procedure.

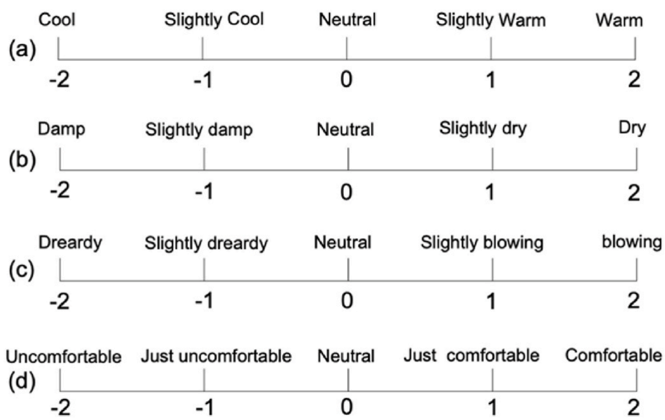

Fig. 3. Scale of the thermal sensation vote (a) and the dampness sensation vote (b) and the wind sensation vote (c) and thermal comfort vote (d) in the experiment.

EEG measurements changed in different contexts, the key channels used reflected human emotions and physical sensations [10,36,37]. The frontal pole (Fp1, Fp2), frontal lobe (F3, F4), parietal lobe (P3, P4), central lobe (C3, C4), occipital lobe (O1, O2), and temporal lobe (T7, T8) were chosen for study under the 64 channels. M1 and M2 were also used for bilateral, mastoid referencing. The [35]electrode distribution is shown in Fig. 4.

The frequency range of the EEG in this study was 0.5–50 Hz. A bandpass filter and notch filter were utilized to filter other EEG noise and 50 Hz interference. Principal component analysis (PCA) was used to correct artefacts such as blinking and muscle activity. Artefacts (e.g., eye blinks and muscle activities) were removed by running the PCA algorithm in ASA [38].

In this study, the absolute, EEG powers were classified by the

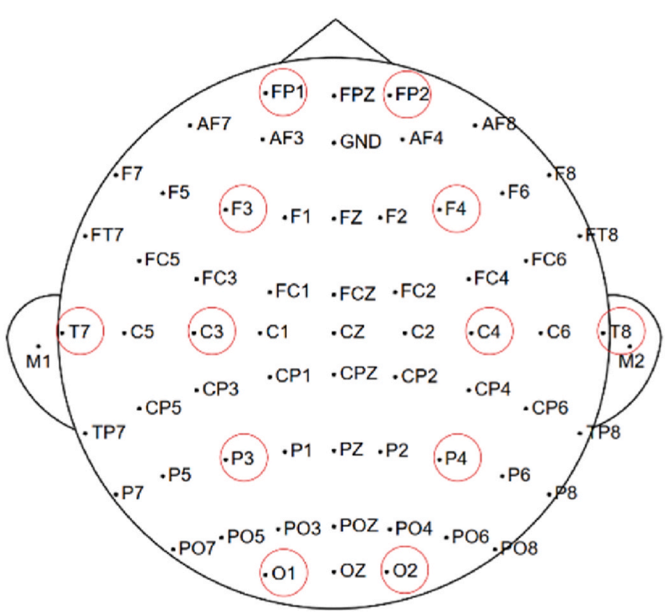

Fig. 4. Electrode placements on the head.

following seven frequency bands that have been generally applied in brain wave studies [8,37]: delta band (δ, 0.5–3.5 Hz), theta band (θ, 3.5–7.5 Hz), low-alpha band (α1, 7.5–10 Hz), high-alpha band (α2, 10–12.5 Hz), low-beta band (β1, 12.5–20 Hz), high-beta band (β2, 20–30 Hz), and gamma band (γ, 30–50 Hz). The obtained EEG powers of the seven bands under different conditions were used in the statistical analysis. The artefact-free, EEG data were divided into 2 s epochs and computed into power spectral density (PSD) [39,40]via a fast Fourier transform (FFT) using ASA.

$$\mathrm{F}[k] = \sum_{n=0}^{N-1} x[n]e^{\frac{-j2\pi kn}{N}}\ k = 0, \dots, N-1 \tag{1}$$

$$\mathrm{P(k)} = \lim_{N\to\infty} \frac{|F(k)|^2}{N} \tag{2}$$

where F is the Fourier transform, x is the signal, and P is the power spectral density.

The seven working circumstances were separated into three groups based on the variations in temperature, humidity, and air velocity. For each of the three combinations, a multivariate two-way ANOVA (environmental x electrode point) was used to determine whether the brainwave bands under distinct, environmental variables played a role overall. The least significant difference (LSD) test was used in post hoc analyses to assess numerical differences at 95% confidence intervals.

Then, the strength of the correlation with the EEG amplitude under different environmental conditions was determined by analysing the power spectral density of the EEG using Pearson correlation coefficient analysis (two-tailed test).

Logistic regression can be applied to measure the probability of an event occurring and has a wide range of applications in the field of thermal comfort [41–43]. In this study, twelve EEG channels were averaged as values for each frequency band, and logistic regression was performed for seven, frequency bands of EEG power spectral density. Logistic regression was used to analyse the EEG power spectral density under all conditions by discriminating the comfort level. Correlation analysis was performed with the comfort-related, EEG rhythm as the independent variable and the probability of thermal comfort as the dependent variable. Logistic regression was developed based on the logit transformation proposed by COX [44]. The assumption of linearity between the independent and dependent variables and the transformation relationship are shown in Eqs. (3)–(6).

$$\text{Logit P} = \ln\left(\frac{\mathrm{P}}{1-\mathrm{p}}\right) \tag{3}$$

$$\text{logit P} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n \tag{4}$$

$$\mathrm{P} = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n)} \tag{5}$$

$$1 - \mathrm{P} = \frac{1}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n)} \tag{6}$$

where P is the probability of thermal comfort, β0, β1, …, βn are the linear coefficients obtained from the regression analysis.

Data management and analysis were performed using SPSS 22.0 (SPSS Inc., Chicago, USA).

3. Results

This section displays the results and analysis of how different indoor, environmental conditions affected the EEG signal. We first presented the statistical results of a two-factor ANOVA to verify the differences in EEG signals in different environments. After that, correlation analysis was used to draw correlations between EEG signals in various environments.

3.1. ANOVA

ANOVA (F test) was used to study the relationship between the independent and dependent variables and the strength of each relationship [45]. The EEG data were log-transformed for all frequency bands to meet the criteria for ANOVA (normality, chi-square, and observation independence).Two-way ANOVA was performed on the EEG data at three levels: temperature, relative humidity, and airflow rate. The independent variables for a two-factor ANOVA were environmental characteristics (three environments with temperature/humidity/airflow rate levels) and measurement point variables (twelve EEG channels connected with somatosensory input). The dependent variable was EEG power in seven frequency bands. Post-hoc analyses (LSD) at various temperatures, humidities, and wind speeds were also conducted.

Differences in the brain activity of participants in each environment were investigated by differences in EEG signals in individual, frequency bands. The effect of EEG power in each frequency band when the environment was altered is analysed in Table 4. In all frequency bands, the EEG activities assessed in response to changes in temperature and airflow rate were substantially different ($p = 0.000 < 0.01$). In the relative-humidity experiment, there were no variations in γ waves ($p = 0.118 > 0.05$), while all other frequency bands had significant differences with significance levels less than 0.05.

The effect of EEG power in each frequency band when the measuring point was altered is analysed in Table 4. EEG activity showed statistically significant changes in the α1, α2, β1, β2, and γ EEG bands for humidity and air velocity at the measuring points. Furthermore, only the α2, β2, and γ EEG frequency bands were altered significantly in the temperature experiment. The other EEG-wave measurement sites, as shown in the table, were not significant.

There was no significant effect of the interaction of all environmental and measuring point variables on EEG amplitude ($p > 0.05$), as shown in Table A. 1.

To determine the significance of the differences among groups, ANOVA with a post-hoc test (LSD) was used. The effect of increasing temperature on the power spectral density of the EEG bands is demonstrated in Fig. 5. When the temperature was raised from 22 °C/ 25 °C–28 °C, the power of all EEG waves changed significantly. However, only the δ, α1, and α2 bands were significantly different when the temperature was raised from 22 °C to 25 °C.

Post-hoc tests of relative humidity illustrated significant differences in the EEG frequency bands of δ, θ, α1, and α2 at 70% RH and 85% RH

Table 4
Effects of the environment or electrode point on electroencephalography power in each frequency band.

ANOVA	Category		SS	Df	MS	F	P
Environment	Temperature	δ	203.788	2	101.894	**41.484***	0.000
		θ	263.317	2	131.659	**114.121***	0.000
		α1	91.114	2	45.557	**36.541***	0.000
		α2	93.735	2	46.867	**35.244***	0.000
		β1	563.956	2	281.978	**274.416***	0.000
		β2	770.647	2	385.323	**365.116***	0.000
		γ	1372.114	2	686.057	**471.944***	0.000
	Relative Humidity	δ	34.968	2	17.484	**7.671***	0.001
		θ	11.420	2	5.710	**5.006***	0.007
		α1	15.934	2	7.967	**7.505***	0.001
		α2	28.443	2	14.221	**14.172***	0.000
		β1	6.264	2	3.132	**3.339***	0.036
		β2	8.450	2	4.225	**4.543***	0.011
		γ	5.201	2	2.601	2.148	0.118
	Air velocity	δ	285.212	2	142.606	**94.887***	0.000
		θ	274.770	2	137.385	**107.14***	0.000
		α1	132.385	2	66.193	**54.211***	0.000
		α2	132.546	2	66.273	**46.948***	0.000
		β1	620.492	2	310.246	**251.251***	0.000
		β2	814.455	2	407.227	**329.889***	0.000
		γ	1454.657	2	727.328	**469.796***	0.000
Electrode point	Temperature	δ	15.923	11	1.448	0.589	0.838
		θ	4.261	11	0.387	0.336	0.978
		α1	18.235	11	1.658	1.330	0.203
		α2	47.275	11	4.298	**3.232***	0.000
		β1	20.048	11	1.823	1.774	0.055
		β2	26.840	11	2.440	**2.312***	0.009
		γ	59.280	11	5.389	**3.707***	0.000
	Relative Humidity	δ	14.938	11	1.358	0.596	0.833
		θ	9.647	11	0.877	0.769	0.672
		α1	35.154	11	3.196	**3.010***	0.001
		α2	69.648	11	6.332	**6.309***	0.000
		β1	50.762	11	4.615	**4.919***	0.000
		β2	48.413	11	4.401	**4.732***	0.000
		γ	89.580	11	8.144	**6.725***	0.000
	Air velocity	δ	18.118	11	1.647	1.096	0.362
		θ	5.928	11	0.539	0.420	0.947
		α1	35.443	11	3.222	**2.639***	0.003
		α2	78.993	11	7.181	**5.087***	0.000
		β1	44.835	11	4.076	**3.301***	0.000
		β2	36.414	11	3.310	**2.682***	0.002
		γ	79.405	11	7.219	**4.663***	0.000

Note: *, $p < 0.05$; SS, Class III sums of squares; df, degrees of freedom; MS, mean squares.

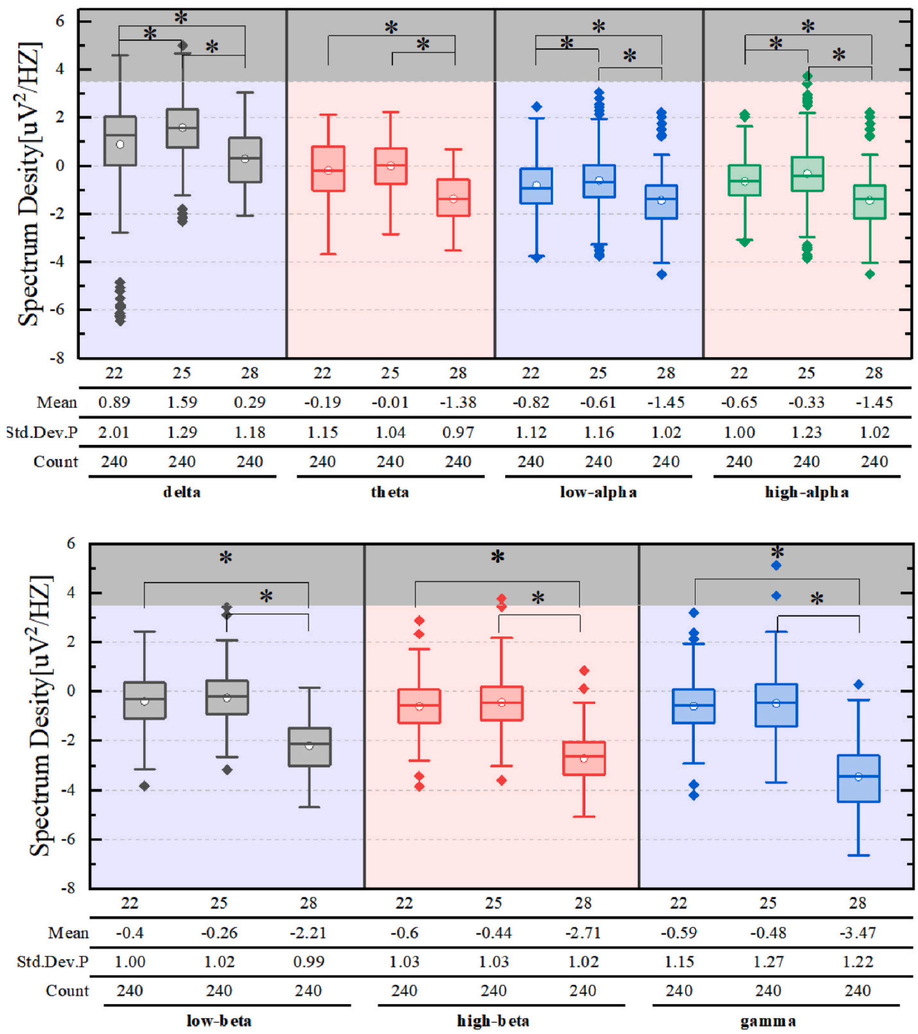

Fig. 5. Response changes in different EEG bands for the temperature experiment (group 1: 22 °C, 60% RH, 0 m/s; group 6: 25 °C, 60% RH, 0 m/s; group 7: 28 °C, 60% RH, 0 m/s).

compared to 60% RH in all bands. In contrast, only 60% RH was significantly different from 85% RH on the β1 and β2 EEG bands (see Fig. 6). γ waves, on the other hand, were not collected.

As shown in Fig. 7, there was a significant difference between wind speed without airflow (0 m/s) on and with airflow (0.5 m/s and 1 m/s) on for each frequency band.

The changes in the power spectral density of brain waves at different rhythms and channels are shown in Fig. 8-Fig. 10. As shown in Figs. 8 and 22 °C and 25 °C showed similar variations in θ, β1, β2, and γ, and it was more different from that of 28 °C. The value of the F3 channel in the high-frequency band was higher at 25 °C. These results presented the effect of temperature on EEG signals. The effect of the humidity experiment on the EEG signal was not significant in the channels (see Fig. 9). Fig. 10 depicts the power spectral density distribution of airflow variation versus electrode site. It showed substantial, associated differences with no airflow (0 m/s) at both 0.5 m/s and 1 m/s consistent with the post-hoc test results. All EEG rhythms showed high similarity at airflow velocities of 0.5 m/s and 1 m/s. Similarly, larger values appeared in the F3 channel at 0 m/s in the high-frequency band.

Based on the p-values, it was evident that environmental impacts on EEG power were in the order of temperature, air velocity, and humidity, and the effects of the measurement site on EEG power were instead in the order of humidity, air velocity, and temperature.

3.2. Correlation analysis

According to Table 1, correlation analyses were conducted for the air-temperature experiment (Groups 1, 6, and 7) as well as the relative-humidity experiment (Groups 1, 2, and 3) and the air velocity experiment (Groups 6, 4, and 5) to find correlations between environmental changes and EEG signals. The findings are shown in Table 5.

The EEG waves revealed a negative association as the temperature increased, with significant correlations in θ ($r = -0.345$, $p = 0.007$), β1 ($r = -0.414$, $p = 0.001$), and β2 ($r = -0.335$, $p = 0.009$). The humidity correlations were not significant, and the correlations were all greater than 0.05. The EEG readings indicated highly substantial, negative correlations in the air velocity experiments.

3.3. Thermal comfort of subjects

Subjects were asked to answer a subjective questionnaire after each completed stage of the experiment. The results of the subjective questionnaire are shown in Fig. 11. The 25 °C, 60% RH, and 0 m/s groups satisfied the individuals' thermal comfort based on their comfort ranges for the thermal comfort scores and other thermal sensations. As a result, Group 6 was designated the "comfort group", while the other groups were designated "uncomfortable." The data were used in the subsequent of data processing steps.

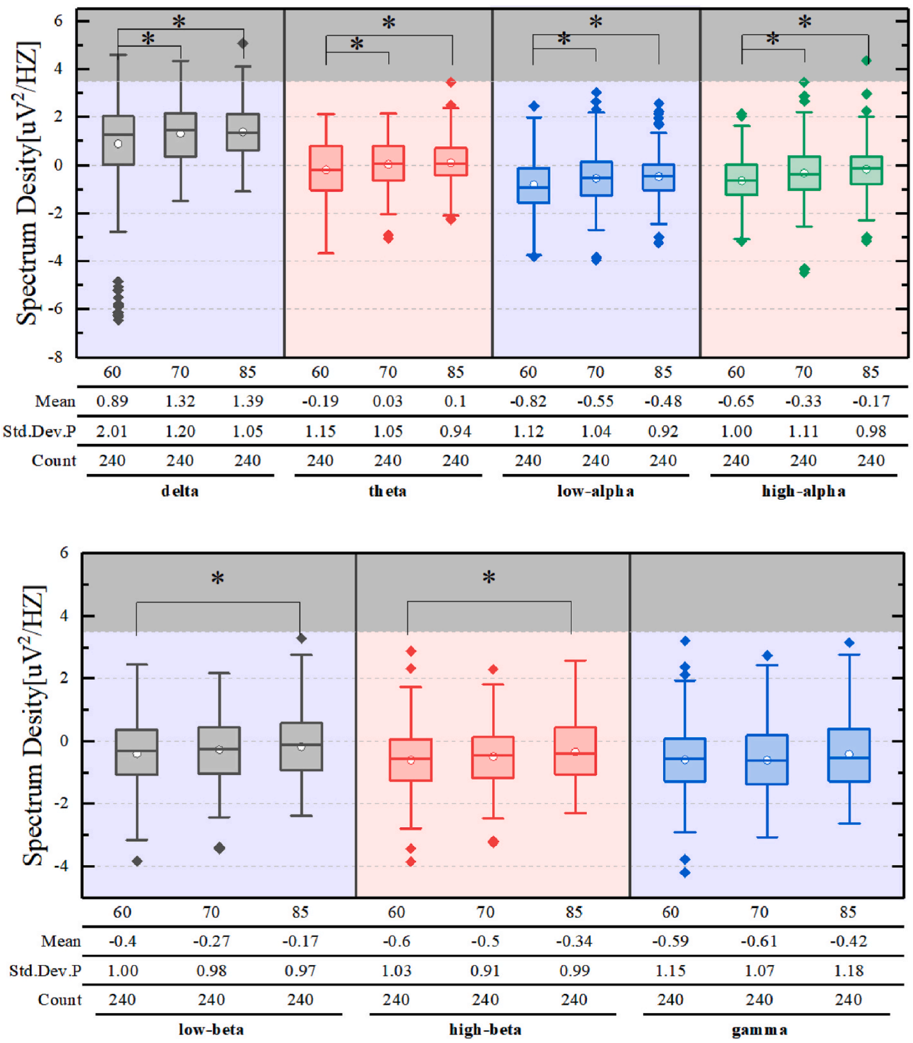

Fig. 6. Response changes in different EEG bands for the relative humidity experiment (group 1: 22 °C, 60% RH, 0 m/s; group 2: 22 °C, 70% RH, 0 m/s; group 3: 22 °C, 85% RH, 0 m/s).

3.4. Logistic regression analysis

Logistic regression can be applied to problems with binary responses. In this study, the conditions were classified as comfortable and uncomfortable based on subjective evaluations as the discriminant criteria. The findings of a correlative study on the grouped data are reported in Table A. 2 with the goal of exploring the EEG channels connected with thermal comfort. Seven EEG cycles were shown to be connected with the δ, β1, and β2 bands being highly correlated. Logistic regression analysis was conducted to examine the two groups of subjects (comfortable and uncomfortable in the thermal environment) who differed in their EEG bands. A binary logistic regression analysis was performed on the data from the entire sample with participants' comfort level as the dependent variable and the δ, θ, α1, α2, β1, β2, and γ bands associated with comfort as the predictor variables for the regression model.

The results in Table 6 show the likelihood ratio test $p = 0.011 < 0.05$, which indicates that the model was generally significant in this fitted model. The Hosmer−Lemeshow test $p = 0.234 > 0.05$ indicated that the model fit was good. The overall, predictive rate of the study model was 88.6%, and the model fit good. Based on the results in Table 6, the regression equation is shown below:(7)

$$\ln\frac{P}{1-P} = -2.492 + 0.086\delta - 0.713\theta + 0.201\alpha_1 + 0.002\alpha_2 + 0.412\beta_1 + 0.386\beta_2 + 0.080\gamma \tag{7}$$

$$P = \frac{\exp(-2.492 + 0.086\delta - 0.713\theta + 0.201\alpha_1 + 0.002\alpha_2 + 0.412\beta_1 + 0.386\beta_2 + 0.080\gamma)}{1 + \exp(-2.492 + 0.086\delta - 0.713\theta + 0.201\alpha_1 + 0.002\alpha_2 + 0.412\beta_1 + 0.386\beta_2 + 0.080\gamma)} \tag{8}$$

where p is the probability that the score is comfortable, 1-p is the probability that the score is uncomfortable.

4. Discussion

The primary objective of this research was to investigate the effects

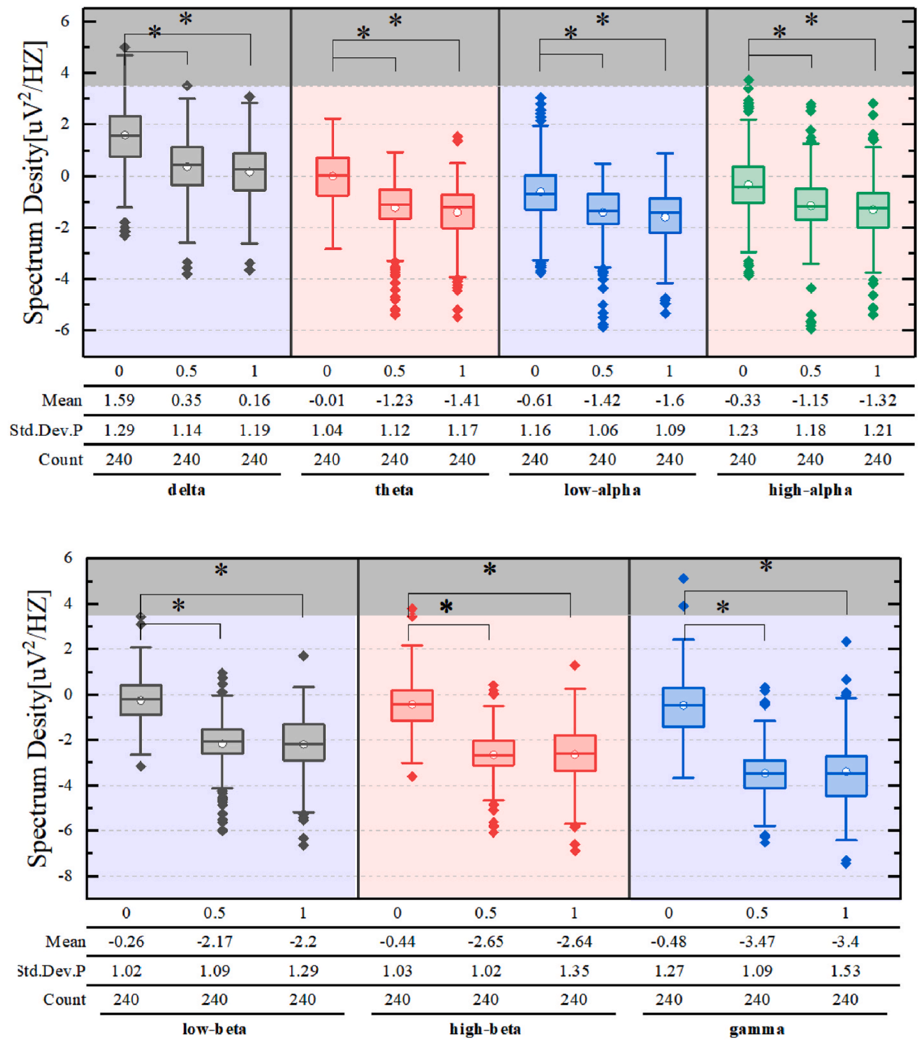

Fig. 7. Response changes in different EEG bands for the airflow rate experiment (group 6: 25 °C, 60% RH, 0 m/s; group 4: 25 °C, 60% RH, 0.5 m/s; group 5: 25 °C, 60% RH, 1 m/s).

of three parameters in the PMV model on the EEG signal using the absolute power spectrum of the EEG signal to investigate how subjects' thermal perceptionis is affected by environmental conditions. In contrast to previous studies, the EEG signal in this study was a task-free, resting-state signal. In addition, logistic regression for comfort discrimination was introduced, and the relational equation between EEG rhythm and comfort was established by classifying comfortable and uncomfortable environmental conditions based on a subjective questionnaire.

4.1. The effect of the indoor environment on EEG signals

In this experiment, temperature had the greatest effect on the EEG signals, followed by air velocity and relative humidity. According to the results of the study, it was found that the trend of change in each measuring point on the θ, β1, β2, and γ bands was similar at 22 and 25 °C and significantly different from 28 °C. This indicates that by using EEG power analysis, high-temperature, thermal sensations can be easily separated from other sensations. The F3 channel showed greater values in the higher frequency band at 25 °C, which can be used as a marker to distinguish other temperatures. There was a significant correlation between the θ, β1, and β2 bands as the temperature increased. One study [46] found that the α and θ bands decrease with increasing temperature. Whereas a part of the literature divides the temperature environment into comfortable and uncomfortable conditions, the β relative power increases when the temperature induces hot and cold discomfort [47]. In a field experiment [9], subjects recorded EEG signals in comfortable and uncomfortable subway environments, and the absolute power of β and γ increased in the uncomfortable subway. Another study [18] specified that relative θ power decreases and relative β and γ power increase in EEG measurements during thermal discomfort caused by high temperatures. Therefore, the β and γ bands can be used to define the temperature-induced EEG signal properties.

The current results showed that EEG signals showed a significant difference between neutral humidity (50% RH) and over 70% RH in experiments with relative humidity. In a experiment conducted on subjects living in areas of varying humidity levels [32], the participants' humidity perception and sweating rate increased significantly when the relative humidity exceeded 70% according to their perception. This indicates that the participants had a significant perception at 70% RH both in terms of EEG signal and subjective awareness. In another temperature-humidity coupling study [23], a sharp increase in the relative power in the δ-band and a significant decrease in other bands was found when the relative humidity increased from 50% to 70% and was independent of the temperature level from 26 °C to 37 °C. The temperature setting of this experiment was 22 °C, but there was no significant change in EEG rhythm with increasing relative humidity. With this inference, it is possible that somewhere in the range of 22 °C–26 °C, the EEG signal is not sensitive to the humidity in the region or is related to the choice of the measuring point.

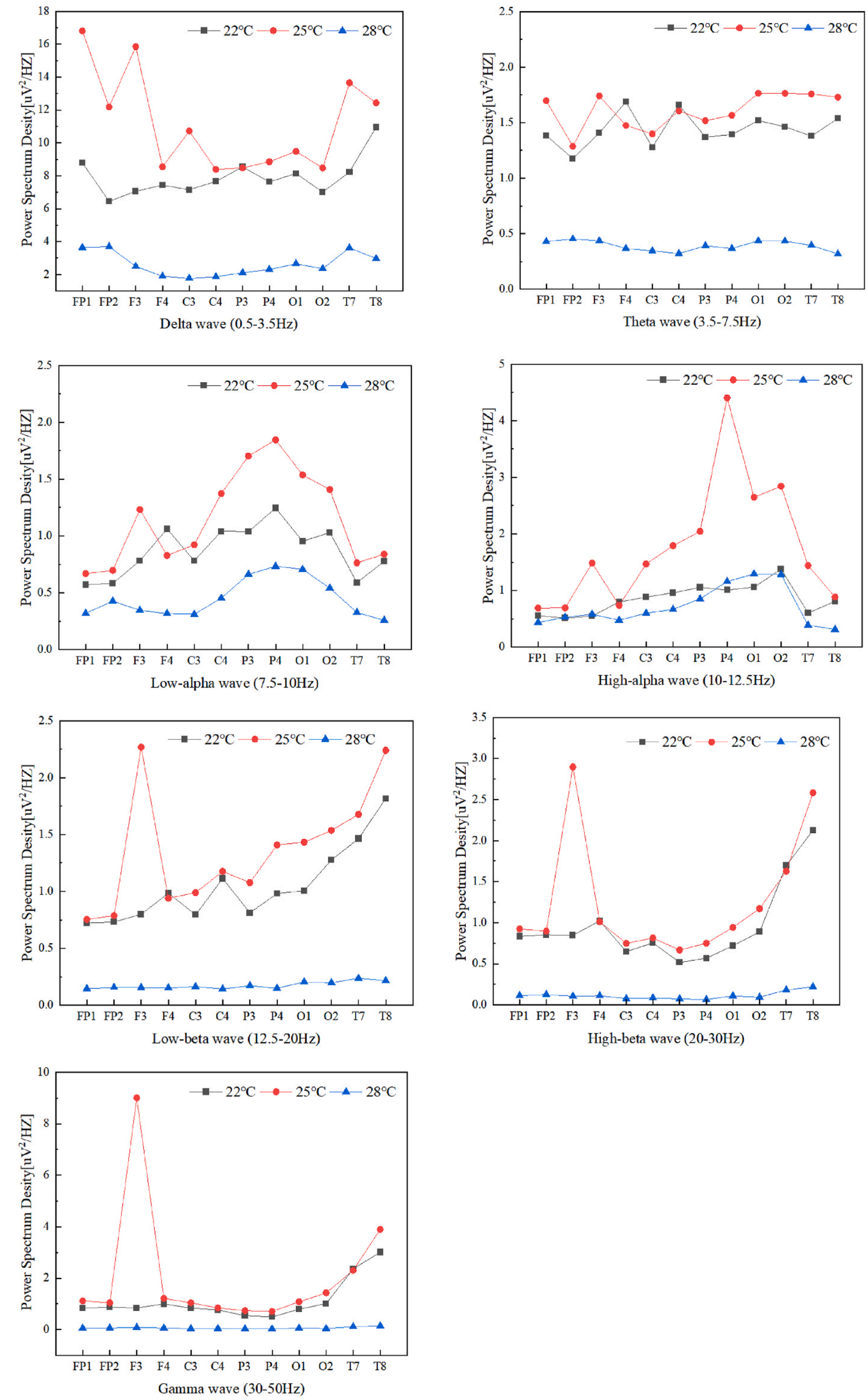

Fig. 8. Distribution of EEG power measured within variable temperature environment.(other parameters: 60% RH, 0 m/s).

In this study, there was a significant difference with and without air velocity but not between the two levels of airflow experiments (0.5 m/s and 1 m/s). In conjunction with a paper on the study of temperature, humidity, and air flow on the thermal response of the body, there seems to be a significant difference between subjective voting on the presence and absence of airflow in the temperature interval of 25–29 °C [48]. Okamoto et al. [25] simulated an experiment in winter and summer under air conditioning and radiation systems to examine the effect of airflow on EEG signals. Under the impact of airflow, considerable variation in the amplitude of the β-band and γ-band was produced, which was independent of the season. In this study, the power of the F3 channel in the 25 °C, 0 m/s, and 60% RH groups was higher than the power of the other channels in the high-frequency band (13–50 Hz), which can be used as an important sign of the effects of this environment.

It is worth mentioning that we used seven brain bands, which were further analysed for α and β. Gwak et al. [37] mentioned the classification of brain bands and stated that the assessment of thermal comfort

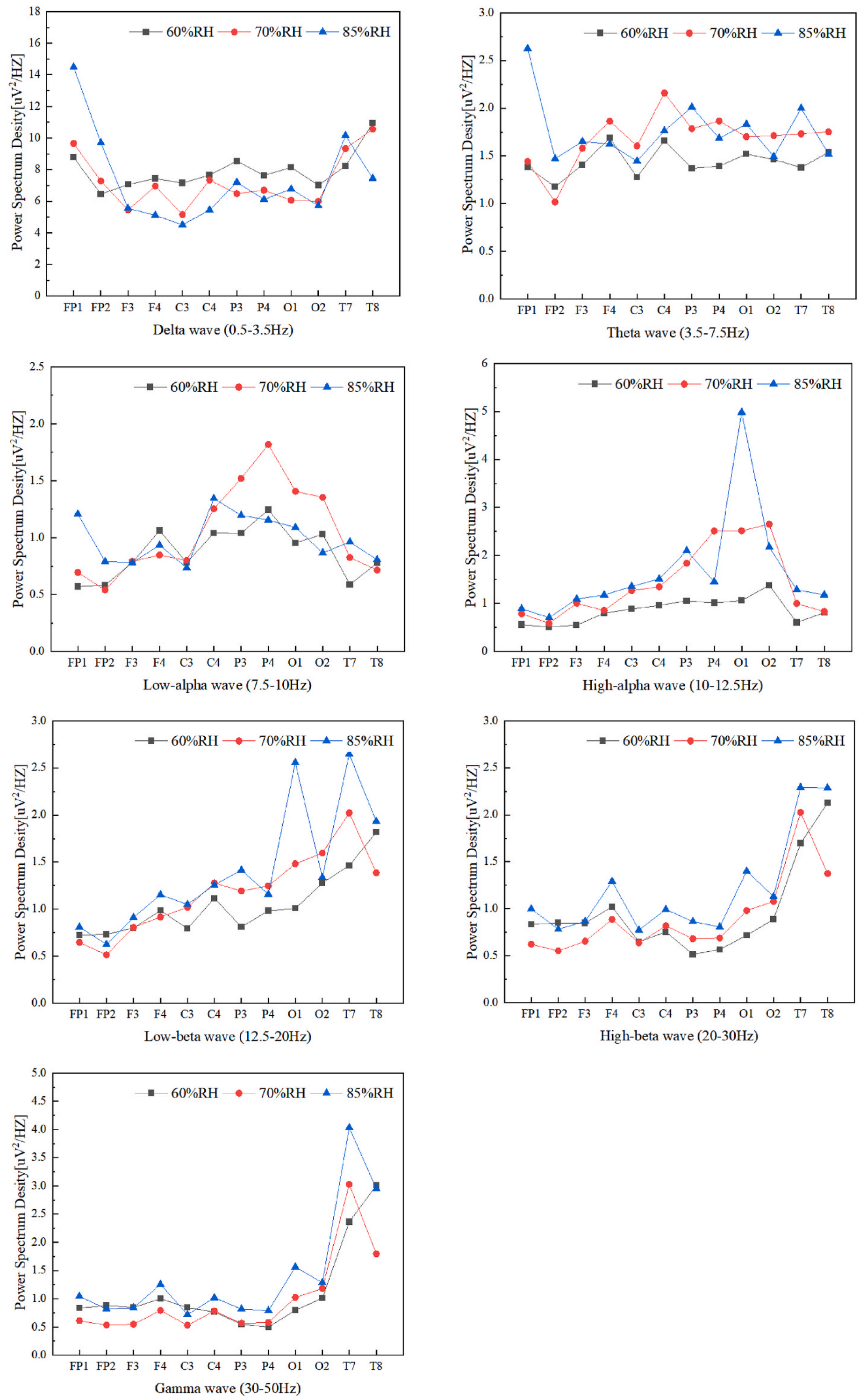

Fig. 9. Distribution of EEG power measured within variable relative humidity environment. (other parameters: 22 °C, 0 m/s).

was correlated with relevant α and high β. Experiments based on temperature levels generated linear regression equations for comfort modelling with C4: α/high β, P4: α/high β, and mean skin temperature (MST) as independent variables; these experiments also generated multiple regression equations. One study [7] collected EEG data in both the working and resting modes to examine the impact of mental tiredness on brain activity. In the resting state, α1 power increased in the frontal and temporal lobes, but α2 power decreased in the parietal lobe, which was also true in the task state. In this study, α and β were further divided into four subwaves α1, α2, β1, and β2, and several meaningful results were obtained. In the temperature experiment, the influence of the measuring point on the EEG signal differed significantly in α2 and β2. It has been indicated that [49] α and low-β power are associated with emotional processing. Further delineation of the α and β bands is therefore essential in the study of EEG experiments to give a clearer picture of the statistical significance of the sub-bands.

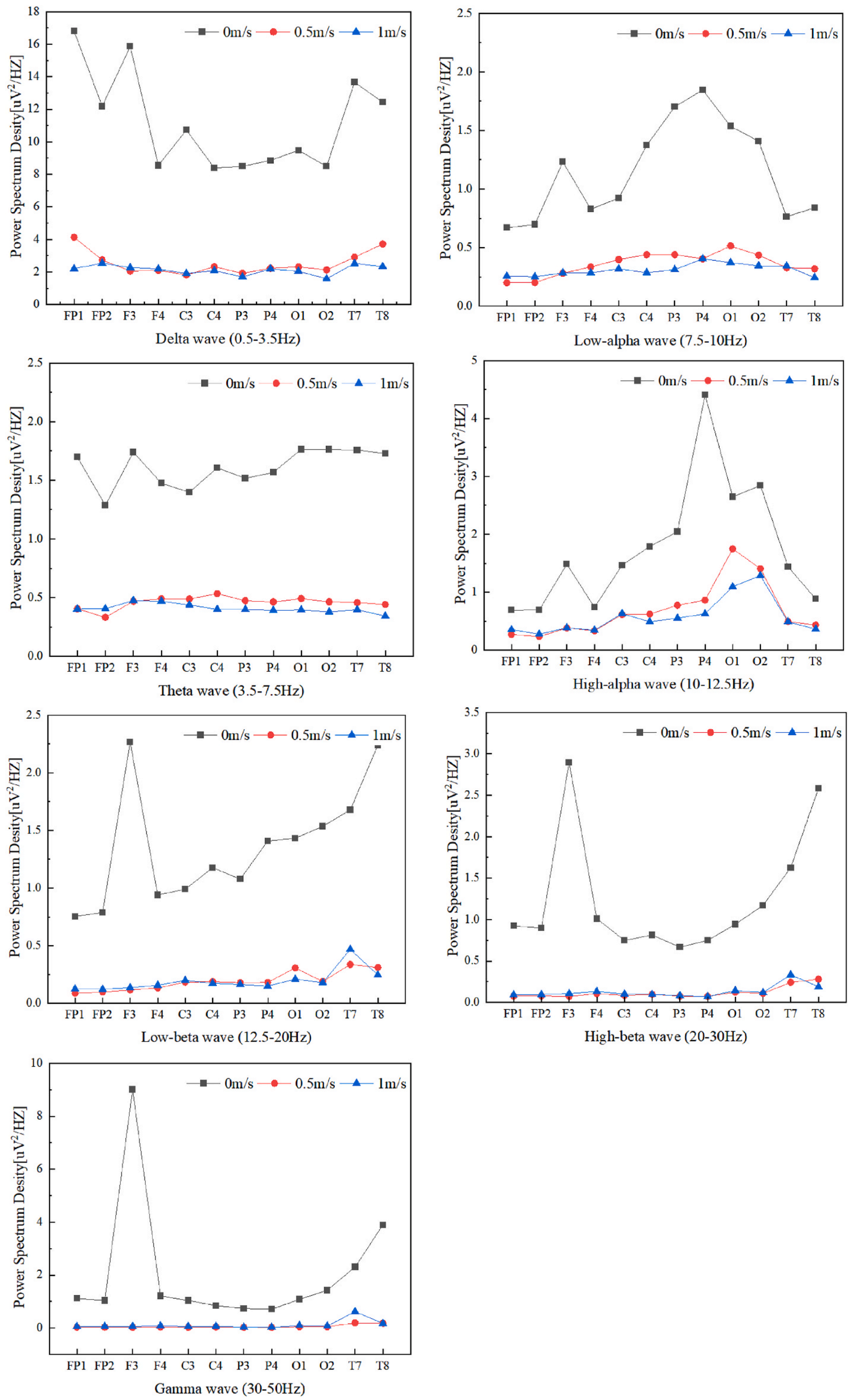

Fig. 10. Distribution of EEG power measured within variable airflow environment. (other parameters: 25 °C, 60% RH).

4.2. Logistic regression for comfort discrimination

According to the correlation analysis, all the EEG rhythms were significant with thermal comfort; however, the crucial brain signals connected with thermal comfort were δ, β1, β2, and γ. δ oscillations have been thought to arise in early human development and are particularly noticeable during slow-wave sleep [50]. In addition, they argued that because the δ rhythm depicts a condition of deep sleep and overlaps with artefacts, the study's analysis of δ bands was completely ignored [25, 51]. However, the researchers concluded in the study [52] that there is a substantial, statistical disparity in both resting- and task-state studies; the amplitude and relative power of δ increased in the fatigued state. The β band is an EEG signal that is connected with active thinking and attention, and the γ band is associated with perceptual and memory awareness [53,54]. According to research [50], the β band increases in size as people become more alert. Neuronal oscillations in the β and γ bands have been demonstrated to correspond with individual, anxiety levels in another study [55]. The brain waves related to thermal comfort

Table 5
Correlation analysis of environment changes and EEG amplitudes.

		Ta	δ	θ	α1	α2	β1	β2	γ
Ta	r	1.000	−0.180	**−0.345**	−0.140	−0.033	**−0.414**	**−0.335**	−0.183
	Sig		0.169	0.007	0.287	0.802	0.001	0.009	0.161
	N	60.000	60.000	60.000	60.000	60.000	60.000	60.000	60.000
		RH	δ	θ	α1	α2	β1	β2	γ
RH	r	1.000	−0.024	0.092	0.039	0.162	0.175	0.129	0.123
	Sig		0.858	0.486	0.767	0.216	0.181	0.328	0.348
	N	60.000	60.000	60.000	60.000	60.000	60.000	60.000	60.000
		Va	δ	θ	α1	α2	β1	β2	γ
Va	r	1.000	**−0.385**	**−0.466**	**−0.334**	**−0.280**	**−0.571**	**−0.488**	**−0.337**
	Sig		0.002	0.000	0.009	0.030	0.000	0.000	0.009
	N	60.000	60.000	60.000	60.000	60.000	60.000	60.000	60.000

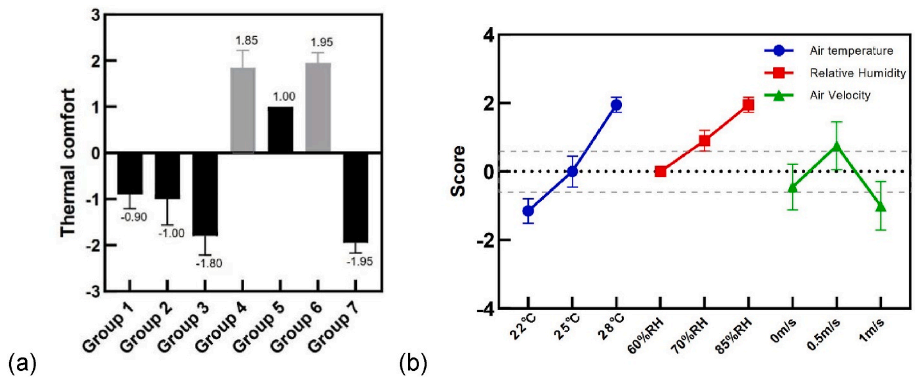

Fig. 11. (a) Scale of the thermal comfort vote. (b) Results of the thermal sensation vote, the dampness sensation vote and the wind sensation vote (N = 20).

Table 6
Coefficient of predictor variables in the equation.

variables	B	S.E.	Wald	df	Sig.		95.0%C.I. for EXP(B)	
						Exp(B)	Lower	Upper
δ	0.086	0.044	1.959	3.838	1.000	0.050	1.090	1.000
θ	−0.713	0.539	−1.321	1.746	1.000	0.186	0.490	0.170
α1	0.201	0.328	0.613	0.376	1.000	0.540	1.223	0.643
α2	0.002	0.251	0.008	0.000	1.000	0.994	1.002	0.612
β1	0.412	0.860	0.480	0.230	1.000	0.631	1.510	0.280
β2	0.386	0.845	0.457	0.209	1.000	0.648	1.471	0.281
γ	0.080	0.425	0.189	0.036	1.000	0.850	1.084	0.471
Constant	−2.492	0.402	−6.197	38.408	1.000	0.000	0.083	

Likelihood ratio test χ^2 (7) = 14.705,p = 0.040
Hosmer-Lemeshow test χ^2 (8) = 10.075,p = 0.260
McFadden R2: 0.128
Cox & Snell R2 : 0.100
Nagelkerke R2 : 0.178
Overall percentage correct for the classification : 88.6%

were also tied with the individual in our study. It has also been demonstrated that the environment's indoor, thermal comfort has an impact on human mood and state of mind.

There are many conclusions addressing the effect of EEG on comfort based on previous literature research. Based on the findings of this study, we believe there are three explanations behind this. The first is the selection of the EEG channels, with the majority of measurement devices used in EEG investigations being international 10–20 systems [8,9,20,21,23,24,46,56,57], making it impossible to pick an EEG signal for assessing thermal comfort. The second reason is whether the EEG power utilized is absolute or relative. In this study, absolute power was used, as we believe that absolute power gives a better demonstration of its relevance, and the conclusions yield a better fit. Kim et al. referenced absolute power in the literature, stating that the power of β and γ increases in uncomfortable settings [9]. The extremely substantial, positive connection provided by β1, β2, and γ in the correlative analysis is similar to the findings described in our correlative analysis. The third reason is the choice of EEG frequency band; most EEG waves are not classified for α and β, but in our study, we discovered that the results provided for α1 and α2 and for β1 and β2 differed.

This paper provides a binary logistic regression equation to discriminate comfort based on the three PMV indicators and human EEG signals, and the overall prediction rate of the study model was 88.6%. By examining a linear mixture of brain waves, the model may be utilized to quantify indoor, thermal settings and determine environmental comfort. In future research, EEG signals could be used to build personal comfort and brain-computer interface applications.

4.3. Limitations

The short duration of the EEG recording was a constraint of this investigation, which was caused by the requirement to coat the wet electrode cap with conductive paste. The result is that the EEG cap cannot be worn for an extended period of time. In addition, the limited sample size resulted in possible individual differences. Finally, because the participants were healthy young male students, more research is needed to see if similar outcomes may be detected in participants of all genders, ages, educational levels, and medical issues.

5. Conclusion

In this paper, the EEG signals of male participants were monitored under changes in temperature, relative humidity, and air velocity to investigate the EEG characteristics of different thermal environments.

The most obvious finding to emerge from this study is that there were highly similar and noticeable border differences in EEG signals in some thermal settings. For the tests on temperature, in the rhythm of θ, β1, B2, and γ, the EEG signals at 22 and 25 °C showed a similar trend, which was significantly different from that at 28 °C. For the experiments on humidity, there was a significant difference between high humidity (70 and 85% RH) and neutral humidity (60% RH) at 0.5–30 HZ. Combined with the relevant literature, it is believed that 70% RH can be used as the cut-off point for high humidity. For the trials on air velocity, the EEG signals were similar for 0.5 and 1 m/s, which were significantly different from the velocity at 0 m/s. In addition, the results showed that the absolute power spectrum of the F3 channel located in the frontal lobe is the most suitable as a single electroencephalogram channel to reflect the 25 °C, 60% RH, and 0 m/s environments, especially its β1, β2 and γ bands. The obtained EEG signals were categorized using subjective, thermal experiences to further determine the EEG channels associated with thermal comfort. All EEG bands were found to be the EEG channels linked with thermal comfort and used to create a binary regression model with an 88.6% discriminant accuracy.

Thermal comfort has been proven to alterhuman EEG signals in our research. To further understand thermal comfort, another PMV parameter that has an environmental impact, namely, the mean radiation temperature, will be included in future studies.

CRediT authorship contribution statement

Liling Pan: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hanying Zheng:** Writing – original draft, Data curation. **Tingxun Li:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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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.2022.109761.

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