

# Thermal Comfort Models for Future Tourism using Heart Rate Variability

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**Abstract:** Current thermal comfort technologies for future tourism, known for their high energy usage, often fall short by creating uniformly neutral conditions that lack efficiency. The key body areas crucial for tourist thermal comfort are the wrists, feet, and head. Thus, there's a pressing need for technologies that specifically target these areas to optimize thermal comfort. Changes in the thermal environment are observed to influence the heart rate variability (HRV) of individuals, indicating fluctuations in their physiological responses to thermal conditions. The primary objective of this study was to identify which HRV indicators significantly affect individual thermal comfort levels. Accurately assessing thermal comfort is essential for energy-efficient environments, yet predicting tourists' thermal comfort proves challenging due to the multitude of influencing factors.

**Keywords:** Future tourism; Thermal comfort; HRV; Regression; Neuro fuzzy JEL classification: Z31, Z38.

## 1. Introduction

Thermal comfort, a subjective state reflecting satisfaction with the surrounding thermal conditions, is traditionally catered to by technologies aiming to establish neutral thermal environments for all occupants [1, 2]. This approach, however, lacks efficiency due to the individual differences among occupants, questioning the rationale behind providing uniform thermal conditions, which also leads to higher energy consumption [3]. It is crucial to recognize that thermal comfort is primarily influenced by the temperature of the head, wrists, and feet, rendering the conditioning of other body parts unnecessary for achieving desired thermal comfort levels [4, 5].

The concept of a personal comfort model introduces a tailored approach to thermal comfort, predicting individual responses rather than relying on average population responses, which is essential for the design and control of thermal environments [6]. Current heating, ventilation, and air conditioning (HVAC) systems use an automatic control strategy to set environmental conditions based on design principles or occupant preferences [7]. To understand human thermal comfort across various settings, continuous electrocardiogram (ECG) monitoring in environments with controlled temperature, humidity, and airspeed is utilized [8]. Among the key parameters in the classic human thermal comfort model, metabolic rate stands out for its significance and the general lack of precision in its assessment in both research and practical applications [9]. For subjective thermal comfort assessment, discrete Likert scales are preferred to minimize intra-individual variances [10]. The Pennes bioheat equation has been employed to examine heat conduction in human tissue under standard thermal comfort conditions [11], highlighting the substantial impact of metabolic rate changes on thermal sensation and comfort [12]. Research indicates no notable difference in thermal sensation and comfort between older and younger individuals [13], while another study explored the use of an infrared thermal camera network to gauge skin temperature and predict occupants' thermal preferences from various distances and angles [14]. The design of side interfaces in buildings, affecting air velocity, plays a significant role in thermal comfort, suggesting that enhancing natural ventilation could improve comfort levels [15]. Physiological factors such as age, gender, and body mass index (BMI) also contribute to an individual's thermal comfort in indoor spaces [16]. Air temperature, followed by relative humidity and air velocity, are pivotal in determining the acceptable range of metabolic rate fluctuations within the thermal comfort zone [17]. Current thermal comfort theories emphasize the importance of metabolic rate and clothing insulation in influencing thermal sensation [18].

Given the subjective nature of thermal comfort, aligning comfort measures with physiological signal fluctuations, such as heart rate variability (HRV), offers a more efficient strategy [19]. Changes in the thermal environment are known to affect HRV, signifying fluctuations in physiological responses to thermal conditions [20, 21]. The study's primary goal is to identify the HRV indices most influential on personal thermal comfort, employing a neuro-fuzzy logic system to address the high nonlinearity between input and output data [22].

## 2. Methodology

HRV indices, as outlined by the Task Force of the European Society of Cardiology and The North American Society of Pacing and Electrophysiology and later revised by the e-Cardiology ESC Working Group and the European Rhythm Association, play a critical role in this study [23, 24, 25, 26]. The process begins with extracting inter-beat intervals from the ECG signal peaks of each participant. These intervals are then analyzed over a 5-minute moving window to compute HRV samples, which are combined to create a comprehensive dataset. New HRV features are generated from this dataset, and a regression analysis is conducted for each HRV index to assess its correlation with thermal comfort factors. The effectiveness of these indices in predicting thermal comfort is evaluated based on the accuracy of the regression models. Thermal comfort is measured in terms of comfort sensation, thermal sensation, and skin sweat sensation, rated by participants on a 0-10 visual analog scale.

The HRV indices used in this study include:

- MEAN\_RR: Mean of all RR intervals (input 1)
- MEDIAN\_RR: Median of all RR intervals (input 2)
- SDRR: Standard deviation of all RR intervals (input 3)
- RMSSD: Square root of the mean sum of squares of differences between adjacent RR intervals (input 4)
- SDSD: Standard deviation of differences between adjacent RR intervals (input 5)
- SDRR/RMSSD: Ratio of SDRR to RMSSD (input 6)
- HR: Heart rate in beats per minute (input 7)
- pNN25: Percentage of adjacent RR intervals with more than 25 ms difference (input 8)
- pNN50: Percentage of adjacent RR intervals with more than 50 ms difference (input 9)
- SD1: Short-term HRV Poincaré plot descriptor (input 10)
- SD2: Long-term HRV Poincaré plot descriptor (input 11)
- KURT: Kurtosis of all RR intervals (input 12)
- SKEW: Skewness of all RR intervals (input 13)
- MEAN\_REL\_RR: Mean of all relative RR intervals (input 14) [27]
- MEDIAN\_REL\_RR: Median of all relative RR intervals (input 15) [27]
- SDRR\_REL\_RR: Standard deviation of all relative RR intervals (input 16) [27]
- RMSSD\_REL\_RR: Square root of the mean sum of squares of differences between adjacent relative RR intervals (input 17) [27]
- SDSD\_REL\_RR: Standard deviation of differences between adjacent relative RR intervals (input 18) [27]
- SDRR\_RMSSD\_REL: Ratio of SDRR\_REL to RMSSD\_REL (input 19)
- KURT\_REL\_RR: Kurtosis of all relative RR intervals (input 20) [27]
- SKEW\_REL\_RR: Skewness of all relative RR intervals (input 21) [27]
- VLF: Very low frequency band of the HRV power spectrum (input 22) [28]
- LF: Low frequency band of the HRV power spectrum (input 23) [28]
- HF: High frequency band of the HRV power spectrum (input 24) [28]
- TP: Total power of the HRV spectrum (input 25) [28]
- LF/HF: Ratio of LF to HF (input 26) [28]
- HF/LF: Ratio of HF to LF (input 27) [28]
- Sample entropy of the RR signal (input 28) [29]
- Higuchi Fractal Dimension (input 29) [30]

The outputs from this study include thermal sensation, comfort sensation, and skin sweat sensation, crucial factors in assessing thermal comfort [22, 23].

### 3. ANFIS methodology

EAs depicted in fig. 1, the Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture is structured into five distinct layers, with the core being the fuzzy inference mechanism. At Layer 1, input variables, denoted as  $x$ , are processed through membership functions to be transformed into fuzzy values. In this particular study, the bell-shaped membership function, defined by equation (1), is selected for its superior performance in nonlinear data regression tasks.

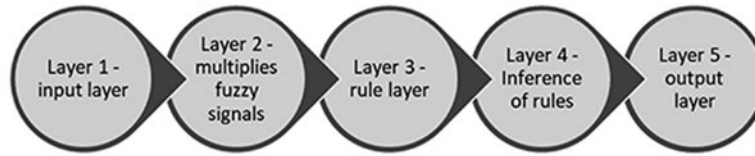


Figure 1: ANFIS layers; Source: [10]

Bell-shaped membership functions is defined as follows:

$$\mu(x) = \text{bell}(x; a_i, b_i, c_i) = \frac{1}{1 + \left[ \frac{(x - c_i)}{a_i} \right]^{2b_i}} \quad (1)$$

where  $\{a_i, b_i, c_i\}$  is the parameters set and  $x$  is input.

Proceeding to Layer 2, the output from the initial layer, which consists of fuzzy values, is subjected to a product operation to determine the firing strength of each rule. Layer 3, often referred to as the rule layer, normalizes these firing strengths, ensuring they are proportionally adjusted across all rules. Layer 4 is responsible for rule inference, where it processes the normalized firing strengths to generate crisp values through defuzzification. Finally, Layer 5 aggregates these crisp values, culminating in a singular output value that represents the system's response to the given inputs.

### 4. Results

Regression models for the thermal comfort estimation are modeled based on neuro fuzzy logic. There are three thermal comfort outputs: thermal sensation, comfort sensation and skin sweat sensation. Tables 2,3 shows ANFIS regression models of the thermal comfort outputs respectively based on single inputs. There are two root mean square (RMSE) values, one for training and one for testing of the ANFIS model. One can see that the regression model with HR (heart rate) has the smallest training RMSE therefore the highest influence on the each thermal comfort output. fig. 3-5 shows ANFIS predicted relationships between HR and given outputs of the thermal comfort.

Table 1. Thermal Sensation regression models:

|                   |                                           |
|-------------------|-------------------------------------------|
| MEAN_RR -->       | training RMSE=1.8203, testing RMSE=1.8824 |
| MEDIAN_RR -->     | training RMSE=1.8159, testing RMSE=1.8835 |
| SDRR -->          | training RMSE=2.0252, testing RMSE=2.0497 |
| RMSSD -->         | training RMSE=2.0316, testing RMSE=2.0654 |
| SDSD -->          | training RMSE=2.0316, testing RMSE=2.0654 |
| SDRR_RMSSD -->    | training RMSE=2.0139, testing RMSE=2.0538 |
| HR -->            | training RMSE=1.7751, testing RMSE=1.8496 |
| PNN25 -->         | training RMSE=2.0427, testing RMSE=2.0428 |
| PNN50 -->         | training RMSE=2.0959, testing RMSE=2.1072 |
| SD1 -->           | training RMSE=2.0316, testing RMSE=2.0654 |
| SD2 -->           | training RMSE=2.0145, testing RMSE=2.0300 |
| KURT -->          | training RMSE=2.0279, testing RMSE=2.0531 |
| SKEW -->          | training RMSE=2.0188, testing RMSE=2.0518 |
| MEAN_REL_RR -->   | training RMSE=2.0572, testing RMSE=2.1019 |
| MEDIAN_REL_RR --> | training RMSE=1.9891, testing RMSE=2.0216 |

SDRR\_REL\_RR --> training RMSE=2.0215, testing RMSE=2.0516  
RMSSD\_REL\_RR --> training RMSE=2.0196, testing RMSE=2.0506  
SDSD\_REL\_RR --> training RMSE=2.0196, testing RMSE=2.0506  
SDRR\_RMSSD\_REL --> training RMSE=2.0484, testing RMSE=2.0777  
KURT\_REL\_RR --> training RMSE=2.0279, testing RMSE=2.0531  
SKEW\_REL\_RR --> training RMSE=2.0188, testing RMSE=2.0518  
VLF --> training RMSE=2.0554, testing RMSE=2.0672  
LF --> training RMSE=2.0347, testing RMSE=2.0526  
HF --> training RMSE=2.0274, testing RMSE=2.0490  
TP --> training RMSE=2.0225, testing RMSE=2.0347  
LF/HF --> training RMSE=2.0718, testing RMSE=2.1016  
HF/LF --> training RMSE=2.0610, testing RMSE=2.0966  
Sampan --> training RMSE=2.0063, testing RMSE=2.0479  
Higuci --> training RMSE=2.0809, testing RMSE=2.1053

The regression models dedicated to predicting comfort sensation, a critical component of thermal comfort, are developed within an Adaptive Neuro-Fuzzy Inference System (ANFIS) framework. These models are specifically tailored to understand and quantify the influence of various physiological and environmental inputs on the perceived comfort sensation.

For each input variable, a separate ANFIS regression model is constructed, aiming to elucidate the complex interactions between the input and the comfort sensation outcome. The performance of these models is quantitatively evaluated using the Root Mean Square Error (RMSE) metric, which is calculated for both the model's training and testing phases. This dual-phase evaluation provides insights into the model's ability to generalize beyond the training data to unseen inputs.

Notably, the models that incorporate Heart Rate (HR) as a predictive variable consistently exhibit lower RMSE values during the training phase. This trend suggests that HR is a particularly potent predictor of comfort sensation, likely due to its direct correlation with the body's physiological stress and comfort levels.

*Table 2. Comfort sensation regression models:*

MEAN\_RR --> training RMSE=2.5815, testing RMSE=2.6167  
MEDIAN\_RR --> training RMSE=2.5778, testing RMSE=2.6203  
SDRR --> training RMSE=2.7549, testing RMSE=2.7644  
RMSSD --> training RMSE=2.7313, testing RMSE=2.7548  
SDSD --> training RMSE=2.7313, testing RMSE=2.7548  
SDRR\_RMSSD --> training RMSE=2.6912, testing RMSE=2.7305  
HR --> training RMSE=2.5512, testing RMSE=2.5946  
PNN25 --> training RMSE=2.7440, testing RMSE=2.7200  
PNN50 --> training RMSE=2.7871, testing RMSE=2.7838  
SD1 --> training RMSE=2.7313, testing RMSE=2.7548  
SD2 --> training RMSE=2.7609, testing RMSE=2.7596  
KURT --> training RMSE=2.7452, testing RMSE=2.7642  
SKEW --> training RMSE=2.7493, testing RMSE=2.7626  
MEAN\_REL\_RR --> training RMSE=2.7638, testing RMSE=2.7891  
MEDIAN\_REL\_RR --> training RMSE=2.7633, testing RMSE=2.7655  
SDRR\_REL\_RR --> training RMSE=2.7105, testing RMSE=2.7351  
RMSSD\_REL\_RR --> training RMSE=2.7036, testing RMSE=2.7298  
SDSD\_REL\_RR --> training RMSE=2.7036, testing RMSE=2.7298  
SDRR\_RMSSD\_REL --> training RMSE=2.6784, testing RMSE=2.7103  
KURT\_REL\_RR --> training RMSE=2.7452, testing RMSE=2.7642

SKEW\_REL\_RR --> training RMSE=2.7493, testing RMSE=2.7626  
VLF --> training RMSE=2.7981, testing RMSE=2.7891  
LF --> training RMSE=2.7495, testing RMSE=2.7551  
HF --> training RMSE=2.7411, testing RMSE=2.7507  
TP --> training RMSE=2.7544, testing RMSE=2.7552  
LF/HF --> training RMSE=2.7569, testing RMSE=2.7767  
HF/LF --> training RMSE=2.7459, testing RMSE=2.7708  
Sampan --> training RMSE=2.7211, testing RMSE=2.7399  
Higuci --> training RMSE=2.7795, testing RMSE=2.7842

Table 3. Skin sweat sensation regression models:

MEAN\_RR --> training RMSE=2.7382, testing RMSE=2.7635  
MEDIAN\_RR --> training RMSE=2.7493, testing RMSE=2.7789  
SDRR --> training RMSE=3.0138, testing RMSE=2.9876  
RMSSD --> training RMSE=3.0306, testing RMSE=3.0181  
SDSD --> training RMSE=3.0306, testing RMSE=3.0181  
SDRR\_RMSSD --> training RMSE=2.9708, testing RMSE=2.9597  
HR --> training RMSE=2.6275, testing RMSE=2.6628  
PNN25 --> training RMSE=2.8857, testing RMSE=2.8250  
PNN50 --> training RMSE=2.9722, testing RMSE=2.9099  
SD1 --> training RMSE=3.0306, testing RMSE=3.0181  
SD2 --> training RMSE=2.9827, testing RMSE=2.9497  
KURT --> training RMSE=2.9822, testing RMSE=2.9635  
SKEW --> training RMSE=2.9807, testing RMSE=2.9665  
MEAN\_REL\_RR --> training RMSE=3.0366, testing RMSE=3.0291  
MEDIAN\_REL\_RR --> training RMSE=3.0285, testing RMSE=3.0101  
SDRR\_REL\_RR --> training RMSE=3.0308, testing RMSE=3.0188  
RMSSD\_REL\_RR --> training RMSE=3.0262, testing RMSE=3.0165  
SDSD\_REL\_RR --> training RMSE=3.0262, testing RMSE=3.0165  
SDRR\_RMSSD\_REL --> training RMSE=2.9981, testing RMSE=2.9735  
KURT\_REL\_RR --> training RMSE=2.9822, testing RMSE=2.9635  
SKEW\_REL\_RR --> training RMSE=2.9807, testing RMSE=2.9665  
VLF --> training RMSE=3.0217, testing RMSE=2.9837  
LF --> training RMSE=3.0299, testing RMSE=3.0114  
HF --> training RMSE=3.0317, testing RMSE=3.0124  
TP --> training RMSE=3.0128, testing RMSE=2.9926  
LF/HF --> training RMSE=3.0671, testing RMSE=3.0394  
HF/LF --> training RMSE=3.0460, testing RMSE=3.0326  
Sampan --> training RMSE=2.9747, testing RMSE=2.9670  
Higuci --> training RMSE=3.0852, testing RMSE=3.0473

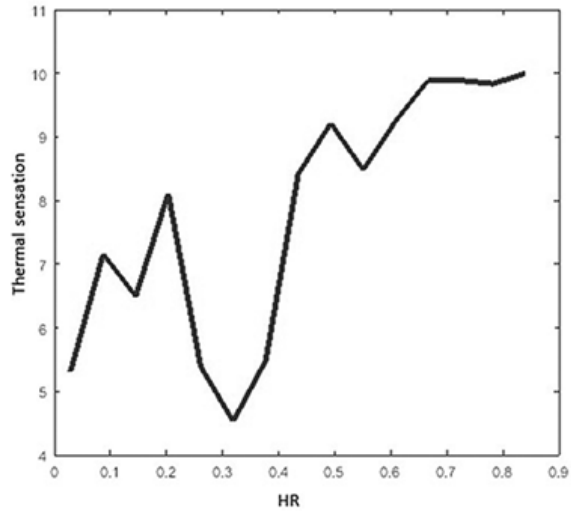


Figure 2: ANFIS predicted relationship between HR and thermal sensation  
Source: Authors' own work

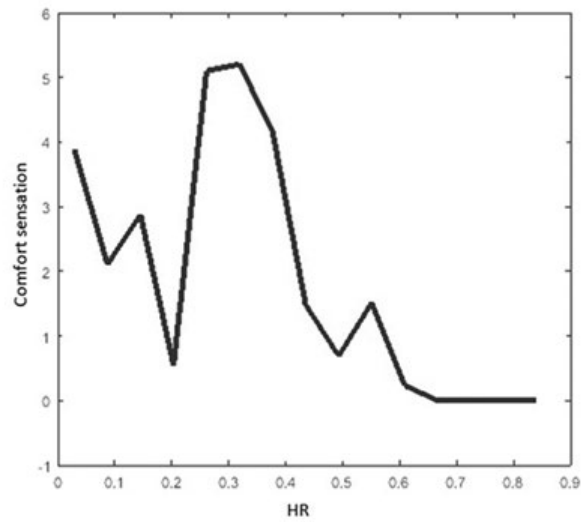


Figure 3: ANFIS predicted relationship between HR and comfort sensation  
Source: Authors' own work

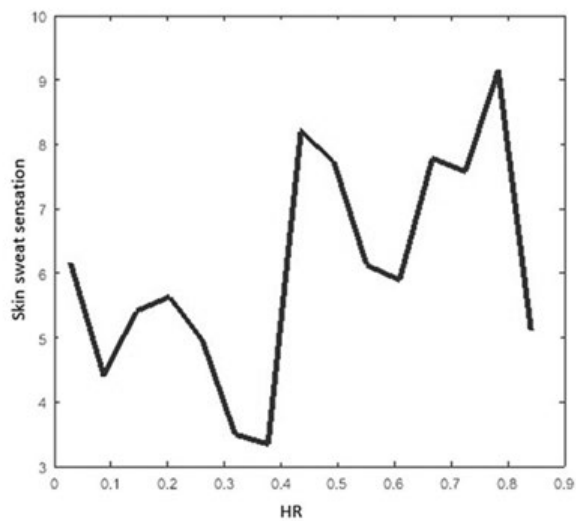


Figure 4: ANFIS predicted relationship between HR and skin sweat sensation  
Source: Authors' own work

## 5. Conclusion

The prevailing approaches to achieving thermal comfort within architectural spaces predominantly revolve around the comprehensive conditioning of entire rooms, either by cooling or heating. This method, while widespread, exhibits significant inefficiencies in energy consumption due to its lack of personalization; it does not account for the individual thermal comfort requirements of each occupant within a space. The nuanced nature of human thermal comfort, inherently subjective and psychophysiological, is influenced by a myriad of factors that vary from one individual to another. Notably, alterations in the thermal environment have been observed to induce variations in the heart rate variability (HRV) of individuals, suggesting a direct link between one's physiological state and their thermal surroundings.

Acknowledging the complex interplay between the thermal environment and physiological responses, this research endeavors to pinpoint specific HRV indices that hold the most substantial influence over individual thermal comfort perceptions. The premise of this study rests on the understanding that thermal comfort transcends mere physical parameters; it is a psychophysiological sensation shaped by diverse and unpredictable elements, rendering broad-brush predictive models inadequate for capturing the intricacies of personal thermal comfort experiences.

To navigate the complexities of this subject, the study adopts neuro-fuzzy logic as its analytical framework. This choice is motivated by the technique's proficiency in managing nonlinear data pairings, a common characteristic of the variables involved in thermal comfort studies. Neuro-fuzzy logic, with its ability to blend the interpretability of fuzzy logic with the learning capabilities of neural networks, provides a robust tool for dissecting the nuanced relationships between HRV indices and thermal comfort.

Through a meticulous analysis, the research unveils that among the various physiological indicators, the heart rate, measured in beats per minute, emerges as the predominant factor affecting an individual's thermal comfort. This finding underscores the critical role of cardiovascular responses in the subjective experience of thermal comfort and highlights the potential for personalized thermal comfort solutions that prioritize energy efficiency and individual well-being.

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