Gender Role in Thermal Comfort Prediction in Industrial Environments Using a Novel XGBoost Approach

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***Abstract*— Global warming has caused significant thermal changes worldwide, increasing electricity demand by 20% to 30% in recent years. This surge disrupts the balance between energy production and consumption, sometimes leading to power outages or blackouts in certain countries. To mitigate this issue, optimizing HVAC systems, which account for more than 40% of global energy consumption, is a key solution, relying on either traditional or AI-based approaches. Our study examines the impact of gender, particularly women's responses, on thermal comfort prediction in industrial environments with a high female presence. Using the ASHRAE RP-884 and Scales Project datasets and applying the XGBoost model, we demonstrated that women's responses achieve the highest prediction accuracy at 68.60%, compared to 62.01% for men and 57.97% for combined responses. Moreover, based on the analysis of responses from different genders in the dataset excerpt, the comfort range for men falls within that of women, suggesting that integrating only female responses into thermal comfort models could enhance HVAC control, productivity, and energy efficiency.**

—*Keywords*—Gender Impact, Thermal Comfort Prediction, Industrial Environments, Women's Sensitivity, HVAC System, XGBoost.

I. Introduction

Optimizing energy consumption in buildings is a critical priority, as this sector accounts for approximately 30% of global energy use and 2% of CO_2 emissions [1]. Heating, Ventilation, and Air Conditioning (HVAC) systems, among the most energy-intensive components of buildings, are responsible for 20% to 40% of a building's total energy consumption [2]. The need for energy-efficient solutions has become even more urgent due to the rising frequency of extreme weather conditions. In 2022, heatwaves and cold spells significantly increased the demand for heating and cooling, despite a reduction in direct emissions from other sectors [3]. However, optimizing thermal comfort is essential not only for reducing energy consumption but also for enhancing occupant well-being. Thermal comfort is influenced by a range of factors, including HVAC settings such as temperature, airflow, and humidity [4], as well as building characteristics like insulation, solar gains, air infiltration, and occupancy levels. Additionally, personal attributes of the occupants, including age, gender, activity level, and individual preferences, play a key role in determining their comfort levels [5]. These diverse and interconnected factors make achieving a balance between comfort and energy efficiency a complex challenge. Traditionally, methods for predicting thermal comfort have relied on mathematical models such as Proportional-Integral-Derivative (PID) controllers and Model Predictive Control (MPC) [6]. More recently, machine learning techniques, such as Support Vector Machines (SVM) [7] and Random Forests [8], have been used to enhance predictive accuracy on tabular datasets. Advanced methods such as LightGBM [9], XGBoost [10], and CatBoost [11] have gained popularity for their robustness, efficiency, and interpretability in real-world applications, providing a solid foundation for the prediction of thermal comfort. Hybrid approaches with handcrafted features and deep learning have shown effectiveness in complex classifications, like medical diagnosis [12], and may improve thermal comfort prediction. Gender differences in thermal perception, particularly in industrial settings, require consideration when optimizing HVAC systems [13], [14].

In this context, the general framework of the proposed approach is illustrated in Fig. 1, which outlines a gender-sensitive thermal comfort optimization strategy aimed at improving well-being and productivity in female-dominated industrial environments. Building upon this framework, the key contributions of this work are:

- Analyzing the impact of various parameters, including gender, on thermal comfort to identify the most relevant features for our dataset.
- Proposing a novel approach based on XGBoost model for thermal comfort prediction and leveraging its ability to capture complex patterns and improve classification performance in industrial environments. The model's effectiveness is assessed using a range of evaluation metrics such as accuracy, F1 score, precision, and recall.

The remainder of this paper is structured as follows: Section 2 reviews related works on thermal comfort prediction and gender differences. Section 3 presents the proposed XGBoost model and the comparative methods. Section 4 provides the experimental analysis, and Section 5 concludes the paper.

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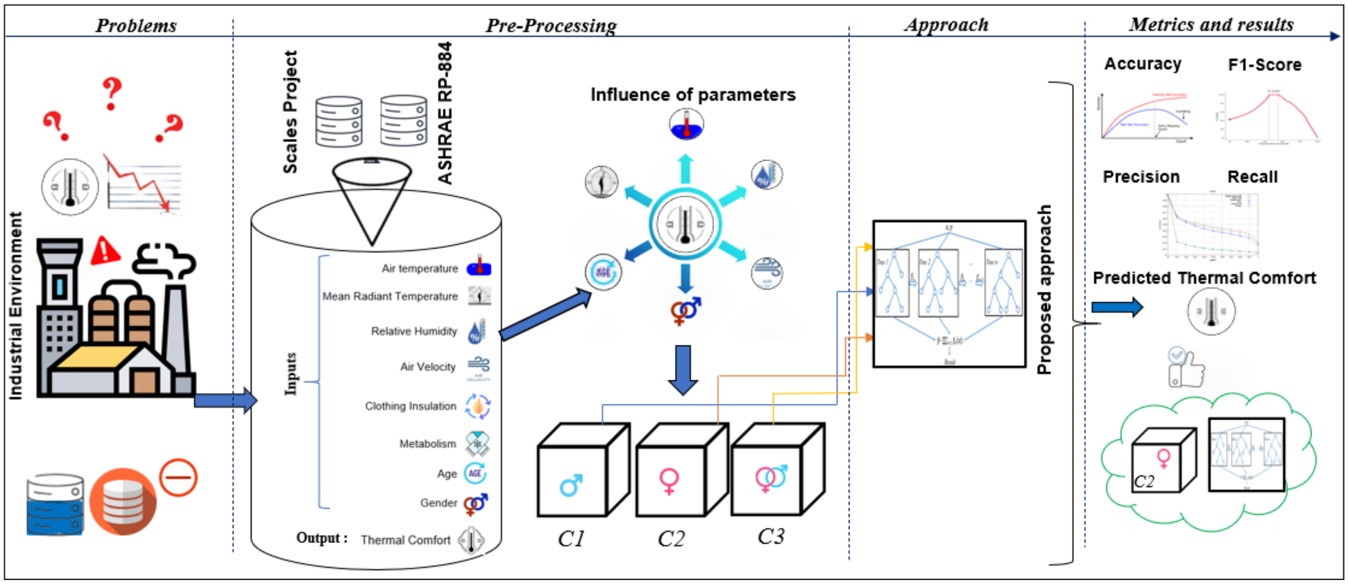

Fig. 1. General layout of the proposed approach

II. Related Works on Thermal Comfort Prediction

This section presents an overview of previous research on thermal comfort, with a particular focus on gender-based differences in thermal perception and behavioral responses in different environments.

Numerous studies have highlighted significant gender-based variations in thermal comfort. For example, Karjalainen [15] investigated gender differences in Finnish homes, offices, and universities. The study, which involved 3,094 participants through surveys and experiments, found that females generally preferred warmer environments and exhibited less adaptive behaviors in response to thermal discomfort. Similarly, research conducted by Indraganti et al. [16] in Indian office buildings further reinforced these findings. Surveying 2,787 participants across 28 buildings, their statistical analysis revealed that both females and older occupants reported lower levels of comfort, suggesting a higher sensitivity to thermal conditions among these groups. In the same vein, Kim [17] examined gender preferences in Asian non-residential buildings. Although the dataset was not specified, the study corroborated previous findings by showing that females preferred higher comfort temperatures compared to their male counterparts. This consistency across different regions underscores the significance of gender in thermal comfort analysis.

Beyond statistical analyses, recent advancements in machine learning have been applied to improve thermal comfort prediction. Nan et al. [18] explored the use of transfer learning for this purpose, utilizing datasets from the ASHRAE RP-884 and the Scales Project. Their study, which implemented transfer learning methods such as TL-Multilayer Perceptron (MLP) and Generative Adversarial Network (GAN) resampling, demonstrated that incorporating gender as a predictive feature enhances model accuracy and performance. In addition to office and residential environments, research has also extended to industrial settings. Indraganti et al. [19] employed IoT sensors to model real-time thermal comfort using artificial neural networks. Their findings highlighted that females exhibited more specific and rigorous thermal preferences, emphasizing the necessity of developing precise models that account for these variations.

While most studies have focused on indoor environments, outdoor thermal comfort prediction has also been explored. Guo et al. [11] developed machine learning models to predict outdoor thermal comfort, demonstrating that shading significantly improves prediction accuracy in unshaded areas.Using a dataset constructed from microclimate measurements and questionnaires, they assessed the impact of key environmental factors, such as radiant and air temperature, on outdoor thermal comfort. Their comparative analysis of different machine learning algorithms XGBoost, LightGBM, and CatBoost demonstrated that CatBoost, when optimized with Bayesian techniques, achieved the highest prediction accuracy, highlighting the importance of both data quality and algorithmic tuning in improving thermal comfort models. Finally, field studies such as those by Adekunle [20] have examined gender-based thermal comfort perceptions in summer conditions. Their findings revealed distinct adaptation strategies between men and women, with women exhibiting more adaptive behaviors in hot environments. This further supports the notion that thermal comfort models must integrate gender-specific behavioral patterns.

These studies collectively highlight the importance of considering gender differences when predicting and managing thermal comfort in various environments. Gender-specific preferences and behaviors significantly influence thermal comfort models and should be taken into account to optimize occupant satisfaction and energy efficiency. The following section outlines the datasets and methods used in this paper.

III. Proposed XGBoost and Comparative Methods for Thermal Comfort Prediction

This section introduces the proposed method along with the comparative models used for thermal comfort prediction. The Tab. I summarizes the models along with their abbreviations.

TABLE I
LIST OF MACHINE LEARNING MODELS AND THEIR ABBREVIATIONS USED IN THIS PAPER

Model	Abbreviation
Support Vector Machine (RBF) [7]	SVM (RBF)
Random Forest [8]	RF
Light Gradient Boosting Machine [9]	LGBM
Ridge Classifier [21]	RC
Categorical Boosting [22]	CatBoost
Extreme Gradient Boosting [10]	XGBoost

A. Technical Characteristics of The Proposed Method (XGBoost)

XGBoost optimizes an objective function presented in Equation 1 that consists of a loss term and a regularization term:

$$\mathcal{L}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t) \tag{1}$$

where $l(y_i, \hat{y}_i)$ represents the loss function, such as log-loss for classification, and the regularization term is given by:

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{j} w_j^2 \tag{2}$$

This regularization helps control model complexity and prevents overfitting.

The boosting process in XGBoost follows an iterative update rule, as shown in Equation 3:

$$F_{t+1}(x) = F_t(x) + \eta h_t(x) \tag{3}$$

where $F_t(x)$ is the current model prediction, $h_t(x)$ is the new weak learner, and η represents the learning rate, which controls the step size of updates.

Several hyperparameters define the behavior of the XGBoost model used in this study. The model relies on tree-based boosting with the XGBClassifier from the XGBoost library, using the learning_rate (η) parameter, which is set to uniform(0.01, 0.2) in a randomized search, controlling the step size of updates and preventing overfitting. The number of boosting rounds (n_estimators) is set to randint(50, 200), allowing for a dynamic number of iterations based on the dataset. Each decision tree can grow up to a maximum depth of 6 (max_depth), chosen to strike a balance between complexity and generalization. The min_child_weight parameter, controlling the minimum sum of instance weights for child nodes, is set to randint(1, 10) to avoid overfitting.

To introduce randomness and prevent overfitting, the subsample parameter is set to uniform(0.6, 0.4), meaning that only 80% of the training data is used per boosting round. Similarly, colsample_bytree is set to uniform(0.6, 0.4), ensuring that each tree uses a randomly selected 80% of the available features. The gamma parameter is set to uniform(0, 1), with no additional loss reduction required for a split. Regularization terms are incorporated: lambda_ (L2 regularization) is uniform(0, 1), while alpha (L1 regularization) is uniform(0, 1).

The model is trained for multi-class classification using the multi:softmax objective function, which directly predicts class labels. To evaluate the model's performance, the merror metric is used, measuring the classification error rate. This configuration is designed to achieve a balance between accuracy, generalization, and computational efficiency, optimized through a randomized search process.

B. Technical Characteristics of Compared Models

- SVM (RBF): employs the Radial Basis Function (RBF) kernel, defined in Equation 4 as:

$$K(x, y) = \exp\left(-\gamma \|x - y\|^2\right) \tag{4}$$

It solves a quadratic optimization problem with a soft margin controlled by the parameter C, which regulates the trade-off between maximizing the margin and minimizing classification errors. A small C allows for a wider margin with more tolerance for misclassification, while a large C results in a narrower margin but fewer misclassifications, making the model more sensitive to noise and prone to overfitting.

- RF: is an ensemble method based on bagging. It constructs multiple decision trees using different subsets of data and features. Predictions are made through majority voting in classification tasks or by averaging in regression tasks. The splitting criterion is based on either Gini impurity or entropy, where Gini impurity is given in Equation 5 as:

$$I(G) = \sum_{i=1}^{K} p_i(1 - p_i) \tag{5}$$

- LGBM: is a gradient boosting algorithm that utilizes a leaf-wise growth strategy instead of level-wise, which improves efficiency and reduces overfitting. The boosting formula is given in Equation 6 as:

$$F_{t+1}(x) = F_t(x) + \eta h_t(x) \tag{6}$$

The loss function for classification is based on cross-entropy, as shown in Equation 7:

$$\mathcal{L} = -\sum_{i=1}^{N} \left[y_i \log p_i + (1 - y_i)\log(1 - p_i)\right] \tag{7}$$

Additionally, it uses a histogram-based splitting strategy and supports L1/L2 regularization penalties.

- RC: is a linear classifier that applies L2-regularization to prevent overfitting. It solves classification problems by minimizing logistic loss with weight decay, as shown in Equation 8:

$$\min_{w} \sum_{i=1}^{n} \log(1 + e^{-y_i w^T x_i}) + \lambda \|w\|^2 \tag{8}$$

- CatBoost: is a gradient boosting method optimized for categorical data. It leverages ordered boosting and oblivious trees. The boosting function is formulated in Equation 9 as:

$$F_{t+1}(x) = F_t(x) + \gamma_t h_t(x) \tag{9}$$

It employs log-loss (cross-entropy) as its loss function and utilizes symmetric decision trees for splitting. A key advantage of CatBoost is its ability to handle categorical features natively, eliminating the need for one-hot encoding.
Each of these models brings distinct advantages and trade-offs. While XGBoost is chosen as our primary method due to its strong predictive power and regularization capabilities, the comparative models serve as benchmarks to evaluate its performance. XGBoost's improvement in our study lies in the careful selection and tuning of hyperparameters, which enhances its ability to prevent overfitting and improves generalization. Specifically, we have optimized the learning rate, maximum depth of trees, and subsampling strategy, among other parameters, which distinguishes our approach from existing implementations. The next section will present the experimental results obtained from applying these models to thermal comfort prediction.

IV. Experimental Analysis

A. Datasets

The study relies on two widely recognized thermal comfort datasets, each providing extensive and diverse data for model evaluation.

- The ASHRAE RP-884 Database [23], with over 25,000 observations from 52 studies across 26 cities, was originally collected to develop the adaptive model by De Dear [24]. It has been widely used in thermal comfort studies.
- The Scales Project Dataset [25] includes responses from 8,225 participants across 57 cities in 30 countries. This dataset aims not only to explore the thermal comfort and acceptability of participants, but also to investigate the validity of assumptions regarding the survey interpretation re- sponses.

Both datasets include key parameters such as indoor air temperature, humidity, air velocity, radiant temperature, clothing insulation, metabolic rate, age, and gender. Thermal comfort, measured on a scale from -3 to +3, was used to assess the occupants' sensations. Extreme sensations, namely +3 and +2, were grouped into a single class +2 (Warm/Hot), while extreme sensations -3 and -2 were grouped into a single class -2 (Cool/Cold). After thorough data cleaning, the datasets were merged to enhance the robustness of our analysis. By including responses from both male and female participants, the study ensures a comprehensive representation of diverse thermal comfort experiences.

B. Influence of Selected Factors on Thermal Comfort

This section discusses the influence of selected factors on thermal comfort, focusing on age, relative humidity, air temperature, radiant temperature, air velocity, and gender. These parameters were chosen for their significant impact on thermal comfort and their practical relevance in industrial settings.

TABLE II
Influence of Parameters on Thermal Comfort

Factor	Influence (%)
Air Temperature	17.58
Radiant Temperature	17.32
Air Velocity	13.60
Relative Humidity	22.07
Age	22.08
Gender	3.60
Metabolic Rate	2.50
Clothing Insulation	2.35

As shown in Table II, age is the most influential factor, contributing 22.08% to thermal comfort, followed closely by relative humidity at 22.07%. Air temperature accounts for 17.58%, while radiant temperature reaches 17.32%, both significantly affecting comfort levels. Air velocity, at 13.60%, plays a key role by improving heat dissipation. Gender has a smaller influence of 3.60%, with a limited impact due to fewer variations in the categories. Metabolic rate and clothing insulation were initially considered but excluded from the final model selection due to their relatively low influence and non-measurability. The selection of parameters such as indoor air temperature, relative humidity, air velocity, radiant temperature, age, and gender ensures the accuracy and applicability of the thermal comfort prediction model in industrial environments, due to their significant impact on comfort and feasibility in real-world settings. To further investigate gender-specific effects, we established three dataset configurations:

- *C1*: Includes all selected parameters, with both male and female participants.
- *C2*: Considers only female participants.
- *C3*: Considers only male participants.

C. Results and Discussion

The results presented in Tables III, IV, and V highlight the impact of gender on thermal comfort prediction and the performance of different machine learning models across various dataset configurations.

TABLE III
Evaluation of different models for thermal comfort prediction Using *C1* Configuration

Model	F1-Score (%)	Accuracy (%)	Precision (%)	Recall (%)
SVM (RBF) [7]	42.18	42.34	45.04	39.67
RF [8]	43.38	43.34	44.60	42.23
LGBM [9]	56.47	55.24	60.18	60.04
RC [21]	33.31	49.71	33.33	49.71
CatBoost [22]	38.33	50.67	48.08	50.67
Proposed XGBoost	**56.70**	**57.97**	**59.45**	**57.97**

TABLE IV

EVALUATION OF DIFFERENT MODELS FOR THERMAL COMFORT PREDICTION USING *C2* CONFIGURATION

Model	F1-Score (%)	Accuracy (%)	Precision (%)	Recall (%)
SVM (RBF) [7]	50.95	51.48	48.72	53.39
RF [8]	53.09	55.07	52.51	53.68
LGBM [9]	56.59	57.70	59.63	57.70
RC [21]	22.30	39.40	15.55	39.40
CatBoost [22]	33.45	42.75	47.10	42.75
Proposed XGBoost	**56.60**	**68.60**	**48.17**	**68.60**

TABLE V

EVALUATION OF DIFFERENT MODELS FOR THERMAL COMFORT PREDICTION USING *C3* CONFIGURATION

Model	F1-Score (%)	Accuracy (%)	Precision (%)	Recall (%)
SVM (RBF) [7]	27.69	38.21	29.65	25.98
RF [8]	39.97	40.37	39.15	40.82
LGBM [9]	56.86	61.19	52.92	64.09
RC [21]	57.44	60.68	57.39	69.68
CatBoost [22]	56.84	60.25	48.20	69.25
Proposed XGBoost	**58.93**	**62.01**	**62.86**	**62.01**

The proposed XGBoost model demonstrates superior performance across all configurations, achieving peak accuracy of 68.60% in *C2* configuration and maintaining strong performance in *C1* configuration with 57.97% accuracy. Notably, the model shows consistent excellence in F1-score metrics, ranging from 56.70% in *C1* configuration to 58.93% in *C3* configuration, outperforming all competing algorithms including LightGBM, Random Forest, Support Vector Machine, Rule-based Classification, and CatBoost.

A significant gender-specific pattern emerges across configurations. Female responses show greater consistency and predictability, particularly evident in *C2* configuration where accuracy reaches its highest point. This finding suggests that female thermal comfort responses exhibit more stable patterns compared to male responses, potentially due to more consistent reporting behaviors or physiological factors.

The performance variations across models reveal important insights about prediction reliability. While XGBoost consistently leads, LightGBM demonstrates strong secondary performance, especially in *C3* configuration with 56.86% accuracy. In contrast, Rule-based Classification shows notable variability, achieving moderate success in *C1* configuration with 49.71% accuracy but struggling with female-only data in *C2* configuration with 39.40% accuracy. This suggests that different modeling approaches capture distinct aspects of thermal comfort patterns, with ensemble methods showing particular strength in handling complex relationships between variables.

These findings carry practical implications for HVAC system optimization. The superior performance with female responses indicates potential benefits in prioritizing women's comfort preferences in industrial settings, particularly where they represent the majority workforce. However, it is possible that the lower performance metrics in male-dominated scenarios suggest the presence of unmeasured factors such as metabolic rate, activity levels, and individual environmental preferences that could enhance future model accuracy.

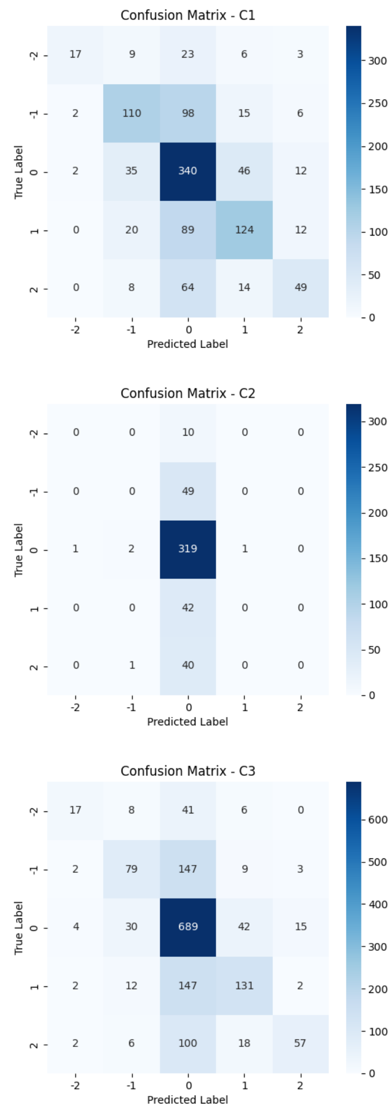

Fig. 2. Confusion matrices for the three dataset configurations: *C1*, *C2*, and *C3*

The comprehensive evaluation underscores the importance of gender-aware thermal comfort modeling. By incorporating gender-specific considerations and leveraging advanced machine learning techniques, particularly gradient boosting methods, building operators can optimize HVAC control strategies while improving both energy efficiency and occupant comfort in industrial environments.

The confusion matrices for the three dataset configurations (*C1*, *C2*, and *C3*) are presented in Figure 2. These reveal notable differences in the XGBoost model's classification performance across gender-specific datasets. In *C1* configuration, which combines male and female responses, the model correctly classifies most neutral responses but struggles with neighboring classes, particularly between -1 and 0 and 1 and 0. In *C2* configuration, the model correctly classifies

319 neutral responses but frequently misclassifies extreme sensations -2 and 2 as neutral, suggesting less variation in female responses. In *C3* configuration, the model correctly classifies 689 neutral responses but shows more dispersion in misclassifications, especially between -1 and 0 and 1 and 0, reflecting higher variability in male responses. These findings emphasize the importance of considering gender differences in thermal comfort prediction models to improve accuracy.

V. Conclusion

The study presented in this paper highlights the significance of gender differences in predicting thermal comfort in industrial environments using measurable variables. Models trained on female responses outperform those based on male or mixed-gender data, with XGBoost on *C2* configuration achieving the highest accuracy of 68.60%, compared to 57.97% for *C1* configuration and 62.01% for *C3* configuration. This suggests that female responses are more consistent, while male responses exhibit greater variability.

Moreover, based on the analysis of responses from different genders in the dataset excerpt, as male comfort conditions often fall within those of females, focusing on female responses enhances predictive reliability. XGBoost consistently outperforms SVM, RF, CatBoost, and RC, confirming its effectiveness in capturing complex thermal comfort patterns.

Integrating gender-aware predictive models in HVAC systems can improve both occupant comfort and energy efficiency. Future work should validate these models in real-world settings to assess their impact on energy savings and occupant satisfaction.

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