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Article

An Experimental Machine Learning Evaluation on Adaptive Thermal Comfort in Hospitals

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Abstract: The healthcare sector is a significant contributor to global energy consumption, particularly within the heating, ventilation, and air conditioning (HVAC) market, due to stringent requirements for maintaining indoor thermal comfort for patients, staff, and visitors in hospital wards, rooms, and intensive care units. This study presents a novel approach employing a Machine Learning-based Linear Regression Algorithm to predict indoor adaptive thermal comfort within the inpatient medical wards. The methodology establishes a robust correlation between key indoor environmental parameters including air temperature, relative humidity, and air velocity, and thermal comfort indices, including Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD). Real-time measurements of indoor environmental conditions were conducted in selected hospitals in Islamabad, Pakistan, utilizing calibrated sensors to capture ambient temperature, wet bulb globe temperature, relative humidity, air velocity, light intensity, and CO_2 levels. This empirical data was integrated with responses from thermal comfort questionnaires, assessing the perceptions of patients, medical staff, and visitors regarding thermal sensation, acceptability, preference, and overall comfort. The adaptive ML-based, predictive analysis identified optimal thermal comfort ranges for hospital wards, recommending indoor air temperatures between 22.0°C and 23.0°C, relative humidity levels between 50% and 55%, and air velocities between 0.1 and 0.2 m/s. The findings revealed a significant impact of overcooling and undercooling on PMV and PPD levels, emphasizing the need for precise HVAC system control to enhance both energy efficiency and occupant comfort. This research contributes to advancing adaptive thermal comfort modeling in healthcare facilities, offering insights for sustainable HVAC management and improved patient outcomes.

Keywords: adaptive thermal comfort; energy management; linear regression; machine learning; predicted mean vote; predicted percentage of dissatisfied

1. Introduction

A hospital can be considered a complex building when compared to other buildings' infrastructure due to the requirement of healthcare units in providing crucial clinical facilities, ensuring patients' needs are met in the most effective manner (Rahman, Zaki, & Husain, 2019). Thermal comfort analysis in healthcare facilities provides a satisfactory insight of an individual whether a patient, hospital medical staff including doctors, nurses, technicians or visitors in terms of improving their comfort level and satisfaction within the hospital's indoor environment (ASHRAE, 2013). The hospital buildings are designed in such a manner to facilitate patients with various health conditions requiring specified indoor environmental requirements as well as a safe and comfortable working atmosphere, vital for the paramedical staff. The highly energy intensive requirements by both patients and hospital staff result in a significant increase in the energy consumption levels owing to the abundance of HVAC facilities, accounting for more than 50% of the total energy consumptions in buildings (P´erez-Lombard, Ortiz, & Pout, 2008). The majority of occupants in hospitals yet remain unsatisfied with the indoor environment (Wang, 2006) and therefore, it becomes necessary to maintain a comfortable indoor environment for occupants', while simultaneously minimizing energy consumption levels (Li, et al., 2023). Latest researches on optimized and energy efficient HVAC systems have yielded novel solutions for both commercial and residential building environments. A study by (Saoud, Boukhchana, & Fellah, 2024) presented a novel solar based single effect lithium bromide (Li-Br) water absorption chiller system which comprised thermodynamic evaluation of design parameters including cooling capacity, COP, and exergy efficiency, followed by heat exchanger effectiveness, and hot source temperatures. An absorber/condenser inlet temperature of 30 °C yielded a high COP of 0.8, Cooling Capacity of 30.05 kW. A Novel Hybrid Indirect Direct Evaporative Cooling (HIDEC) System was experimentally tested for hot and dry and hot and dry subtropical climate, yielding the lowest supply air temperature of 24.8 °C, a maximum COP of 35.2 (Khan, et al., 2024). The HIDEC system was developed considering the thermal comfort ranges within the built environments, with measured elevation in dew point effectiveness to 80% and wet bulb effectiveness to 85%.

Another Research proposed the integration of a single effect double lift absorption chiller system modelled using thermodynamic parametric analysis yielding optimal cooling capacity of 106.1 kW, utilizing low grade heat energy with notable temperature difference in the driving heat stream of 10 times, approx.36.0 °C instead of 3.5 °C notably enhancing cold generation (Saoud, Bruno, Boukhchanaa, & Fellah, 2023). A study presented the Numerical modelling of a novel single effect absorption refrigeration system (ARS) with a cooling capacity of 16 kW using the Engineering Equation Solver, incorporating lithium bromide and water as working fluids (Saoud, Boukhchana, & Fellah, 2024). The parametric analysis of the ARS indicated the absorber temperature being the key variable in energetic efficiency regulation of the chiller system.

The development of an accurate thermal comfort model is necessary to attain a comfortable indoor environment with reduced energy consumption levels. Two basic thermal comfort models are utilized in evaluation of indoor thermal environment in buildings including the static and adaptive comfort models. The static model introduced by P.O. Fanger utilized the heat balance equation, recommended for air-conditioned indoor spaces where the impact of thermal environment was considered to be indirect (Fanger, 1970). The static method constitutes the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) thermal comfort model incorporated as per the ASHRAE standard—55 which formulates indoor thermal comfort condition requirements, notably the 80% satisfaction threshold of occupants in indoor built environments (ASHRAE, 2020). PMV is mainly used in the evaluation of human satisfaction and thermal comfort levels accredited by both ASHRAE and ISO 7730 standards (International Organization for Standardization, 2005). The PMV index incorporates both indoor environmental and subjective parameters (Zare, et al., 2018). Indoor environmental parameters comprise of indoor temperature, indoor relative humidity, mean radiant temperature, and indoor air velocity whereas the subjective parameters consist of metabolic rate and clothing insulation (CLO) (Ozbey & Turhan, 2023).

The other model being utilized by various researchers in thermal comfort analysis is the adaptive thermal comfort model which incorporates the impact of outdoor climatic conditions on the indoor thermal comfort level of occupants due to the aptitude of indoor occupants in adapting to various climatic and temperate conditions during the annual seasonal shifts (Dear & Brager, 1998; Nicol & Humphreys, 2002). The conventional thermal comfort models are based on statistical techniques which utilize experimental data in predicting thermal comfort levels however, such methods often give considerable prediction errors (Maier & Marggraf Micheel, 2015; Chan & Chau, 2021). Some researchers use computational fluid dynamics (CFD) developing indoor thermal and environmental conditions to achieve thermal comfort prediction results (Nimarshana, Attalage, & Perera, 2022; Javad & Navid, 2019); however, such methods require a lot of computational power and multiple iterations to yield convergence making the overall process time consuming due to slower simulation speeds. The latest advances in data sciences and emergence of Artificial Intelligence have led to many researchers adopting Machine Learning (ML) algorithms in formulating thermal comfort prediction models (Chaudhuri, Soh, Li, & Xie, 2020; Jia, Choi, Liu, & Susman, 2022).

The ML thermal comfort models are used to evaluate the relationships between the thermal sensation feedback provided by occupants and the impact of parameters by themselves, without any prior information on the physical impacts of each factor due to the self-learning ability of the model (Zhou, et al., 2020). Moreover, such models are able to rectify or adjust the comfort relations within the parameters themselves, when applied to different scenarios due to their self-correction ability. The ML thermal comfort models provide the analyst the possibility to test different input combinations and obtain the most optimum parameter or test set; moreover, ML based thermal comfort models can be incorporated in average based models as well as Personal Comfort Models (PCMs) (Fard, Zomorodian, & Korsavi, 2022).

2. Literature Review

The notable merits of the recently investigated ML based thermal comfort analysis and its implementation in building indoor thermal environment and energy management, particularly in hospitals, has been of interest to many researchers. A comprehensive review by (Wang, et al., 2021) explored key issues including the non-uniformity and divergence in research objects or features, diversified ML based algorithms, limited data resource collection and methodologies, non-uniformity in data structures, tech-oriented research shifts, insufficient adaptability of ML model and lack of confidence by model user. Reviewing latest studies on ML based thermal comfort analysis can help researchers further identify potential research gaps and working domains with an intra-comparison of different ML algorithms being implemented and the occupants' response. In a research by (Luo, et al., 2020), a comparison was made between the performance of different ML algorithms, and it was suggested that building parameters including building type, building operation modes, and climatic conditions did not remain amongst the top ranked parameters considering their impact. Nevertheless, these parameters had their effect on the thermal perception of occupants and required further investigation considering their impacts.

A research by (Shan, et al., 2020) outlined that an occupant possessed its unique thermo-regulation mode and an individual response to thermal stress, making it necessary to develop Personal Comfort Models (PCMs) for an independent occupant based, thermal comfort analysis and prediction. A recent study by (Ilmiawan, Zaki, Singh, & Khalid, 2024) on personalized thermal comfort (PTC) utilized desk fans as an airflow medium in conjunction to the air conditioning in building which allowed maintenance of thermal comfort of occupants at a personal level. An investigation on impact of wind speed and direction upon thermal comfort and occupants' skin temperature under regulated personalized occupant space at 29.0 °C using air conditioning was made which allowed mapping of different body parts of the occupant targeted for wind movement to achieve thermal comfort ranges. A research by (Gong, et al., 2023) developed an Artificial Neural Network (ANN) based ML model which effectively predicted the in-patients' personalized thermal sensation in rehabilitation wards of a general hospital in Xuzhou, China. The ANN thermal comfort model effectively predicted the thermal sensation of patients, and it was also identified that the inclusion of spatial and health relevant parameters into the ANN model yielded an improved prediction accuracy estimated at 8.10% higher than the baseline model.

A study by (Ma, Wang, Ye, Wang, & Dong, 2023) utilized Deep Learning (DL) algorithms in developing direct and indirect thermal comfort prediction models in real time. The indirect DL based prediction model incorporated the Bi-directional Long Short-Term Memory (Bi-LSTM) algorithm in the prediction of indoor environmental parameters and the thermal comfort real time prediction results were evaluated using the PMV calculation methodology. The accuracy, robustness and performance of DL based Bi-LSTM model was analyzed and compared using different time scales, whereas the impact of indoor air temperature and relative humidity prediction uncertainty on the overall thermal comfort prediction accuracy was analyzed for a 10 min, 30 min, and 60 min time interval. The accuracy of the DL based Bi-LSTM model in thermal comfort prediction on smaller time scale was higher than larger time scale during which RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) reached 0.0551 and 0.0543 on the 10 min scale. The Bi-LSTM model was recommended for integration in control modelling of HVAC systems thus being a reference during optimization of indoor thermal comfort analysis.

An empirical study conducted by (Ma, Deng, Lu, Zhou, & Liu, 2023) in dental treatment departments within four hospitals in Ningbo, China investigated the current thermal environment, thermal sensation of hospital staff, seasonal variation of metabolic rate in occupants and clothing insulation (CLO). Adaptive thermal comfort models for dentists were developed providing a comparison between thermal environment and comfort in public hospitals and private clinics. The thermo-neutral temperature was derived using PMV and TSV regression, Griffith's method, and thermal comfort temperature range. The preferred operating temperature for hospital staff was evaluated using the adaptive predicted mean vote (aPMV) model. The research yielded favorable comfort temperatures which in comparison were lower than the established adaptive threshold but remained closely aligned with the temperature ranges suggested for healthcare and hospital buildings design considerations.

An investigation on comfort temperature and thermal adaptation of patients and visitors in three different Malaysian hospitals outlined a mean comfort indoor operative temperature of 25.3 °C for patients and 25.5 °C for visitors (Khalid, Zaki, Rijal, & Yakub, 2019). The analysis yielded a cost saving potential for hospitals and enhanced thermal comfort of hospital occupants by increased indoor set-point temperatures. A research investigated the applicability of steady-state thermal comfort methodology in hot climate zones conducted specifically on 120 hospital patients in Jeddah, Saudi Arabia (Alotaibi, Lo, Southwood, & Coley, 2020). The study comprised environmental monitoring and assessment of cumulative thermal comfort parameters with simultaneous estimation of CLO and metabolic activity levels for patients admitted in surgical and medical wards. The study outlined a significant variance in results of TSV assessed using patient surveys and questionnaires, and the PMV assessed during physical measurements. The TSV approach failed to yield an independent neutral temperature due to TSVs being extremely scattered, and the attempts made to incorporate regression in determining correlation between operative temperature and TSV failed ultimately. The PMV index gave a neutral temperature of 25.6 °C using regression and Griffith's method yielding a mean temperature of 22.7 °C.

This study investigates adaptive thermal comfort using the adaptive predicted mean vote (aPMV) model, validated through machine learning-based linear regression. The analysis incorporates parameters such as ambient temperature, relative humidity, air velocity, and CO_2 levels. Conducted from May 2023 to February 2024 at the Pakistan Air Force (PAF) hospital in Islamabad. The study examines thermal comfort in sub-tropical climatic conditions using real-time data collected from medical wards, ICUs, and isolation wards. Thermal sensation, comfort levels, adaptive behaviors, and clothing insulation (CLO) were assessed through patient surveys, with a nominal CLO value of 0.5 assumed to represent typical hospital attire. The findings demonstrate that overcooling occurs when relative humidity exceeds 60% and operative temperatures drop below 22.0 °C, resulting in negative PMV values (−0.5 to −0.7) and increased PPD (Predicted Percentage of Dissatisfied) levels, while undercooling is observed at relative humidity below 55% and operative temperatures between 23.0–24.0 °C, yielding neutral PMV values (+0.2 to +0.4) and reduced PPD levels. These results emphasize the significance of adaptive HVAC controls in maintaining thermal comfort and recommend future research to integrate dynamic CLO variations for greater accuracy in comfort evaluations.

3. Materials and Methods

The study was conducted in Islamabad, which lies in the humid subtropical climate zone, having four seasons giving both dry, and humid composite climatic conditions. The field assessments were carried out during both summer and winter seasons in different male and female wards, intensive care units, isolation wards, and maternity wards of the Pakistan Air force Hospital located in Islamabad Capital Territory outlined in Figure 1.

The study incorporated a valid sample size of 85 respondents including patients, doctors, nurses and hospital staff. The healthcare sector, including public and private hospitals in the Islamabad capital territory were contacted for field measurements and surveys. However, the scope of the study had been narrowed down to private hospitals owing to longer administrative approval processes in public hospitals. The field measurements time period spanned over the months of June 2023-August 2023 (summer climate), and December-February 2024 (winter climate). The consent of the hospital management was taken initially where the details and objectives of the study were discussed. After the approval, the Engineering and Maintenance department was contacted for the authorization of field measurements to be conducted in the hospital. The study was conducted in different hospital wards with each patient surveyed only once in a transverse or cross-sectional technique.

Figure 1. A Panoramic view of the Pakistan Air force Hospital, Islamabad.

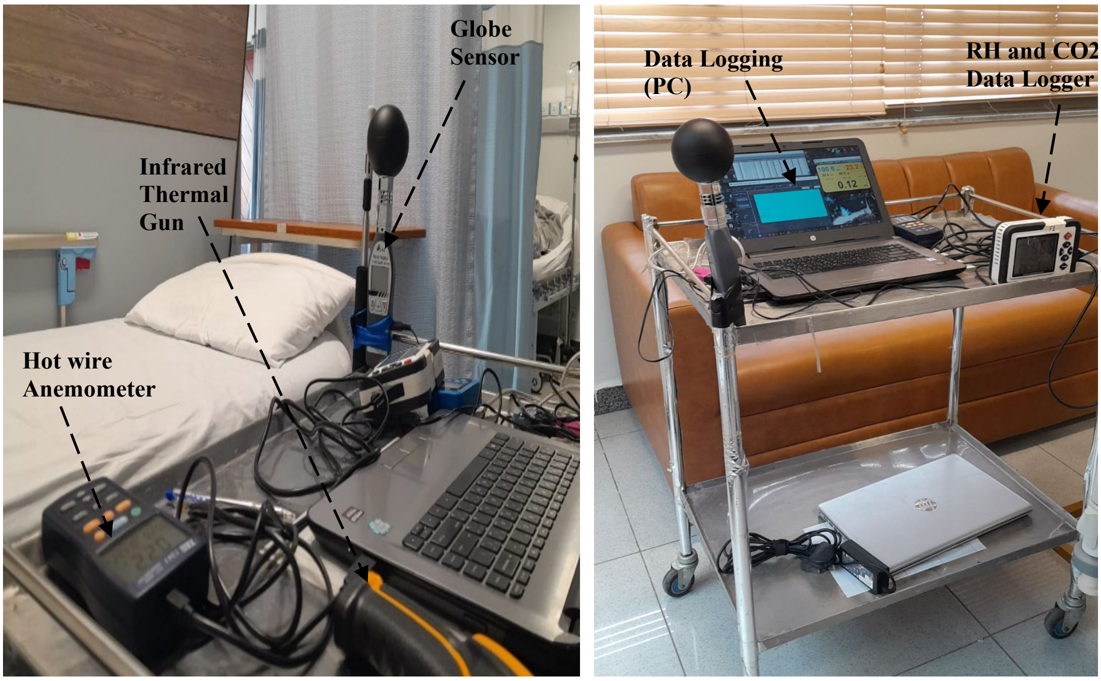
3.1. Experimental Setup

Details of equipment used for thermal environmental measurements are outlined in Table 1.

Table 1. Instruments and their specifications utilized in thermal comfort field assessments.

Parameter	**Symbol**	**Instrument**	**Accuracy**
Indoor Air Velocity	V_a	TES 1341 Hot Wire Anemometer	± 2%
Indoor Relative Humidity	RH_a	HT 2000 HTI Digital CO_2 / Temperature / RH Data Logger	± 3%
Indoor Air Temperature	T_a		± 0.6 ºC
Indoor Carbon Dioxide Level	$CO_{2(air)}$		± 50 ppm
Indoor Wet Bulb Globe Temperature	T_{wbgt}	AZ 8778 Handheld Wet Bulb Globe Temperature Meter	± 0.6 ºC
Indoor Globe Temperature	T_g		
Indoor Light Intensity	I_{lux}	LT 505 EXTECH Light Meter	± 3%
Wall Temperature	T_{wall}	AS 530 Smart Sensor Infrared Thermometer	± 2%

The sensors utilized during thermal comfort analysis were placed near the patient on a movable trolley with a standard height maintained at 1.2 m from ground level during patient's sitting/reclining position on bed. The sensors were set to obtain thermal comfort measurements at a sampling rate of 1 s (1000 ms) and synchronized with the data logging software as shown in Figure 2a and b. Each sample set was set to a 10 min time interval of indoor environmental data recording, during which the thermal comfort surveys were distributed and filled as per patient's preference.



(a) **(b)**

Figure 2. (**a**) Equipment layout during field assessments placed parallel to patient bed (**b**) Data logging activated during thermal comfort field assessments.

The real-time indoor environmental data obtained from the sensors was incorporated in the checklist as shown in Table 2. The checklist outlined the coordinates and dimensions where survey was taking place including the time of survey, floor no., ward type, room area, no. of occupants, current air conditioning state, duct temperature, wall surface temperatures.

Table 2. Checklist outlining thermal comfort measurements during field assessments.

Ward: Gynae						**Floor** 5^{th}			**Corridor Temperature (˚C)** 24.3								**Weather** Hot and Humid			
			Close [0] Open [1] Semi [0.5]			**Off [0] On [1]**			**Surface Temp. $T_{surface}$ (˚C)**						V_a	I_{lux}	T_a	RH_a	T_g	$CO_{2(air)}$
Room Area	No. of Persons	Date / Time	Internal Door	Blind	AC type	Cooling	Ceiling Light	Duct	Ceiling	Floor	East	West	South	North	m/s	lux	ºC	%	ºC	ppm

3.2. Thermal Comfort Survey

The Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) are evaluated using the Center for the Built Environment (CBE) Thermal Comfort Tool (Tartarinia, Schiavon, Cheung, & Hoyt, 2020). The thermal comfort parameters including PMV and PPD are evaluated using experimental real time datasets including indoor relative humidity and indoor operative temperature. The thermal comfort assessment surveys were designed considering the ASHRAE 55 and ISO 7730 thermal comfort standards. Table 3 outlines the main indicators used in assessing hospital occupants' health, thermal and humidity preference, comfort, air flow vote (AV) and preference, and the thermal sensation vote (TSV). The TSV and AV scales of −3 to +3 were followed within the hospital setting, allowing for the categorization of occupants' thermal sensation and air flow preference levels (−3, −2, −1, "0", +1, +2, +3).

Table 3. Thermal comfort questionnaire survey scales.

Scale	Health status	Thermal sensation vote (TSV)	Thermal pref. (TP)	Overall comfort (OC)	Humidity feeling	Humidity pref.	Air flow vote (AV)	Air flow pref.	Air flow accept. vote
6				Highly comfortable					
5				Slightly Comfortable					
4	Well			Comfortable					
3	Fair	Hot		Slightly uncomfortable	Highly humid	Highly dry	Strong air flow		
2	Unwell	Warm	Considerably cooler	Uncomfortable	Moderately humid	Moderately dry	Moderate air flow	Lowest air flow	
1	Sick	Slightly Warm	Slightly cooler	Highly uncomfortable	Slightly humid	Slightly dry	Weak air flow	Lesser air flow	Yes
0		Normal	No change		No change	No change	No movement	No change	
−1		Slightly Cool	Slightly warmer		Slightly dry	Slightly moist		Higher air flow	No
−2		Cool	Considerably warmer		Moderately dry	Moderately moist		Highest air flow	
−3		Cold			Highly dry	Highly moist			

The experimental data including indoor thermal comfort environmental measurements were gathered using real-time data recording sensors whereas the thermal comfort questionnaires were simultaneously filled as per patient's preference within the recording time interval of 10 min as shown in Figure 3.

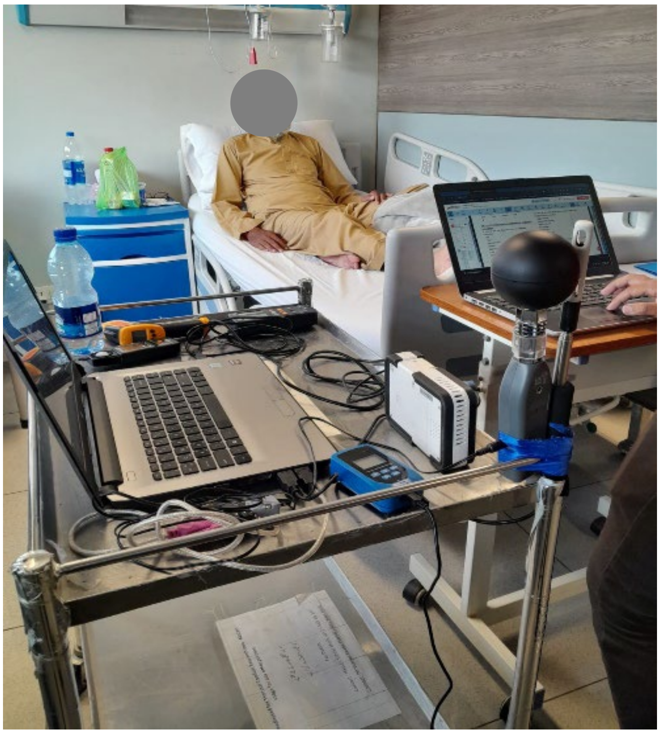
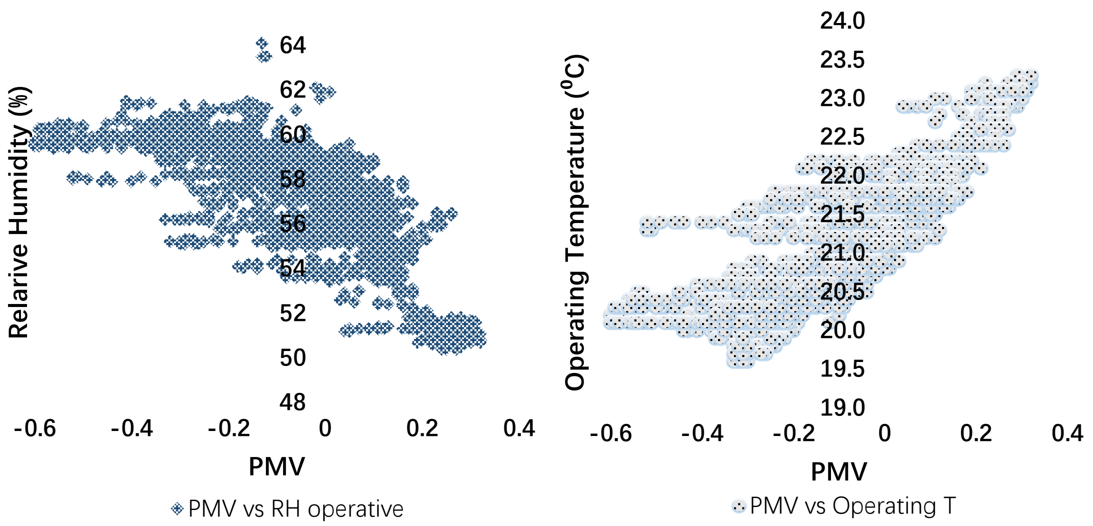


Figure 3. Questionnaire being filled with simultaneous real-time data-recording.

4. Results and Discussion

The Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) are evaluated using the Center for the Built Environment (CBE) Thermal Comfort Tool (Tartarinia, Schiavon, Cheung, & Hoyt, 2020). The PMV and PPD parameters were estimated by incorporating experimental real time datasets including indoor relative humidity and indoor operative temperature. PMV is observed to increase in a negative trend with values approaching −0.6 indicating the hospital's HVAC chiller system's overcooling, done to reduce the indoor temperature without impacting indoor relative humidity levels.

A highest negative PMV of −0.6 observed at 60% relative humidity indicated in Figure 4a, which gradually increases to a maximum positive of +0.3 with an associated reduction in relative humidity level to approx. 50% indicating the undercooling of hospital's HVAC system. The patients admitted in hospital wards had complained of lower set point temperatures resulting due to overcooling of the HVAC system as observed in Figure 4b where PMV falls to a negative of −0.6 at lowest indoor operating temperature of 20.0 °C. However, PMV is also observed to rise to approx. +0.3 with a gradual increase in indoor operating temperature to 23.0 °C indicating undercooling of the HVAC system.



(a) **(b)**

Figure 4. PMV vs Relative humidity (**a**), and PMV vs Operating temperature (**b**).

The Predicted Percentage of Dissatisfied (PPD) levels indicate that patient dissatisfaction reached its peak, ranging between 12–13%, at the lowest operating temperatures (set point) of approximately 20.0 °C, as shown in Figure 5a. This dissatisfaction is attributed to overcooling by the HVAC system. Furthermore, the increased indoor humidity levels, estimated between 60–62% and exceeding the comfort range, exacerbate patient discomfort, as depicted in Figure 5b. Occupants in inpatient hospital wards reported discomfort when the central HVAC system, operating at peak load, supplied conditioned air at excessively low temperatures (16.0–18.0 °C), particularly during late-night hours. This discomfort is reflected in the higher PPD values at supply air temperatures below 20.0 °C. Additionally, the chiller system's air humidification process further elevated relative humidity levels within the hospital wards, with maximum RH levels exceeding 60–62%, contributing to overall dissatisfaction.

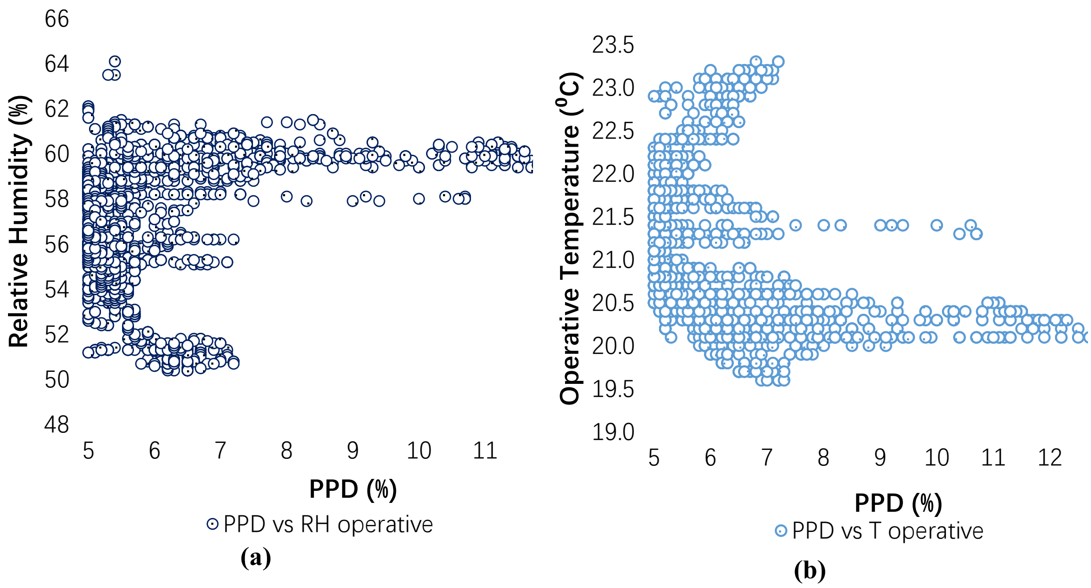


Figure 5. PPD vs. Relative humidity (**a**), and PPD vs operative temperature (**b**).

The indoor air velocity parameter is observed to fluctuate within 0 to 0.5 m/s. An increase in air velocity enhances convective heat transfer from the human body and occupants' including the inward patients which reduces Predicted Mean Vote (PMV) conforming to the findings reported in literature (Khalid, Zaki, Rijal, & Yakub, 2019). At higher airflow rates, the indoor air velocity reaches 0.3 to 0.5 m/s, resulting in the lowest PMV values of approximately −0.6, indicative of the hospital's HVAC system overcooling, as shown in Figure 6a. This overcooling reduces overall occupant satisfaction within the inpatient wards, as evidenced by elevated Predicted Percentage of Dissatisfied (PPD) levels, reaching 11–13%, as shown in Figure 6b. The neutral point (0 PMV) is achieved at optimal air velocity levels between 0.1–0.2 m/s, during which PPD is at its lowest (7–8%). Conversely, when the indoor air velocity drops below 0.1 m/s, PMV values begin to rise, reaching a maximum of 0.3, indicating the HVAC system's slight undercooling. However, this slight undercooling has minimal impact on PPD levels.

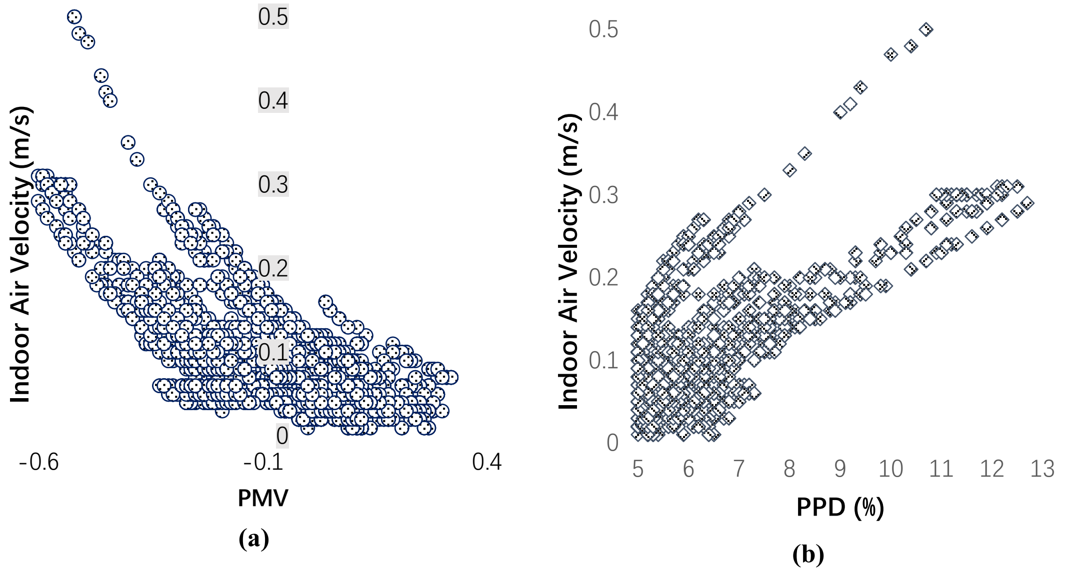


Figure 6. Indoor Air Velocity vs PMV (**a**), and PPD (**b**).

Hospital patients reported excessive overcooling within hospital wards indicated by the PMV following a negative trend approaching −0.6, indicating the overcooling of hospital's HVAC chiller system, done to reduce the indoor temperature without impacting indoor relative humidity levels. This is reflected in the maximum plot scatter within the negative PMV range of −0.2 to −0.6, leading to an increase in PPD levels from 5.0% to 13.0%. The correlation between PMV and PPD, as shown in Figure 7, further highlights that patient dissatisfaction remained minimal (0 to 0.4 PPD) when the HVAC system was operating at slightly undercooled conditions with higher operative temperatures, suggesting better alignment with thermal comfort preferences under such circumstances.

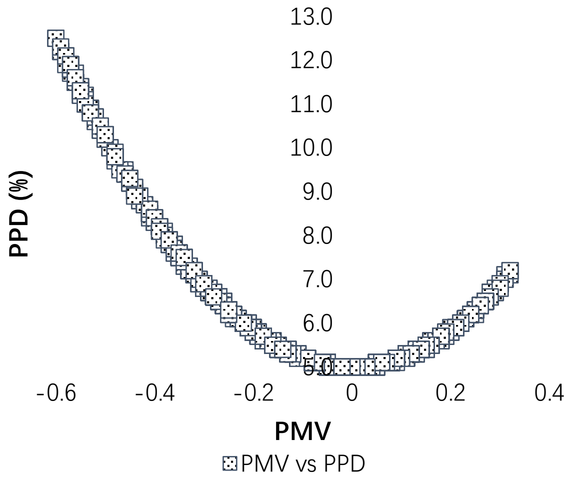


Figure 7. Graphical Comparison between PMV and PPD thermal comfort parameters.

Linear regression statistical measures and performance metrics are outlined in Table 4 and Table 5 respectively, including the correlations between PMV and Predicted PMV, PPD and Predicted PPD with the Ambient Air Temperature, Relative Humidity and Air Velocity Parameters. Error metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R^2 Score have been illustrated. A comparison is made between the statistical (ANOVA) and Regression Metrics (Python ML approach).

Table 4. Linear regression coefficients and performance metrics illustrated considering PMV.

Regression Statistics								
Multiple R	0.992267							
R Square	0.984593							
Adjusted R Square	0.984577							
Standard Error	0.022378							
Observations	3914							
Linear Regression (ANOVA)							Linear Regression ML Model (Python)	
	df	*SS*	*MS*	*F*	*Significance F*		Mean Absolute Error (MAE)	0.017312
Regression	4	125.1014	31.27536	62452.44	0		Mean Squared Error (MSE)	0.000473
Residual	3909	1.957576	0.000501				Root Mean Squared Error (RMSE)	0.021747
Total	3913	127.059					R^2 Score	0.984207
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	−4.85696	0.05151	-94.2919	0	−4.95795	-4.75598	-4.95795	−4.75598
ta	0.125283	0.001681	74.55022	0	0.121988	0.128578	0.121988	0.128578
tr	0.089592	0.001124	79.72415	0	0.087389	0.091795	0.087389	0.091795
vel	-1.64332	0.005876	−279.666	0	−1.65484	−1.6318	−1.65484	-1.6318

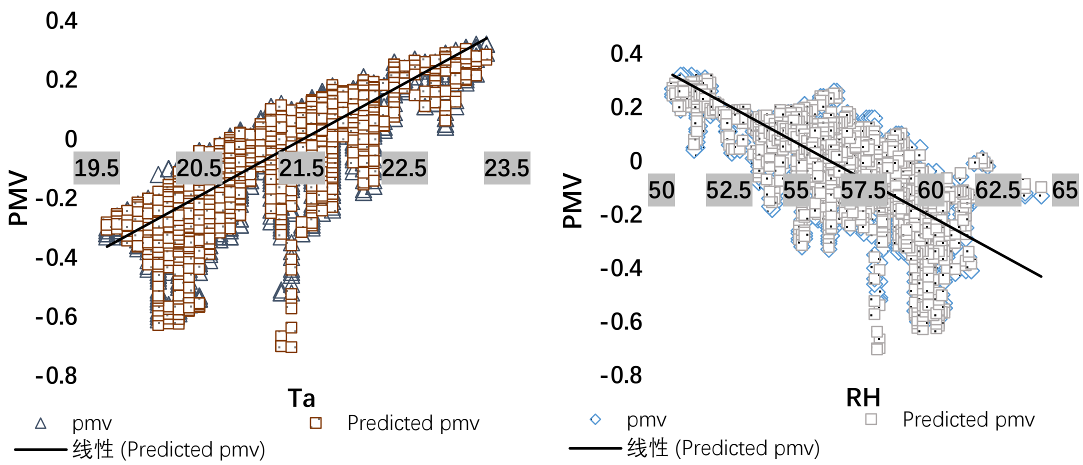
rh	0.00616	0.000425	14.5074	1.72E-46	0.005327	0.006992	0.005327	0.006992

Table 5. Linear regression coefficients and performance metrics illustrated considering PPD.

Linear Regression Metrics							
Multiple R	0.828886						
R Square	0.687053						
Adjusted R Square	0.686733						
Standard Error	0.686387						
Observations	3914						
Linear Regression (ANOVA)						Linear Regression ML Model (Python)	
	df	**SS**	**MS**	**F**	**Signific. F**	Mean Absolute Error (MAE)	**0.505968**
Regression	4	4043.198	1010.799	2145.488	0	Mean Squared Error (MSE)	0.473603
Residual	3909	1841.639	0.471128			Root Mean Squared Error (RMSE)	0.688188
Total	3913	5884.837				R^2 Score	0.714859
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	38.6486556	1.579914	24.46251	4.3E-123	35.55112273	41.74618848	35.55112	41.74619
ta	0.328905613	0.051545	6.380958	1.97E-10	0.227848238	0.429962988	0.227848	0.429963
tr	−1.529054321	0.034469	−44.3608	0	−1.596632442	−1.4614762	−1.59663	−1.46148
vel	13.36056412	0.180229	74.13103	0	13.00721228	13.71391595	13.00721	13.71392
rh	−0.141281787	0.013023	−10.8484	4.91E-27	−0.166814968	−0.115748605	−0.16681	−0.11575

Linear regression predictive modeling, utilizing machine learning, revealed key correlations between the PMV index, operative temperature, and relative humidity. As shown in Figure 8a, maintaining an indoor temperature of 23.0–24.0 °C alongside relative humidity levels between 50–55% results in a PMV index range of +0.2 to +0.4, indicative of slight undercooling and optimal thermal comfort for hospital occupants. This observation underscores the significance of balanced indoor temperature and humidity control in meeting thermal comfort standards. However, overcooling occurs when supply air temperatures drop below 22.0 °C, as the HVAC system reduces operative temperatures without adequately addressing indoor humidity levels. This limitation arises from the system's lack of an integrated dehumidification mechanism, which hinders its ability to maintain appropriate humidity levels.

Figure 8b outlines that relative humidity levels below 55% are associated with positive PMV values, reflecting effective thermal regulation under slightly undercooled conditions. In contrast, as relative humidity exceeds 60%, resulting from the saturation of the chiller system at lower setpoint temperatures, PMV values shift into negative ranges, signifying overcooling and increased occupant discomfort. These findings reveal that the hospital's HVAC system prioritizes temperature reduction at the expense of humidity control, exacerbating thermal discomfort. Incorporating a dehumidification system would address this shortcoming, allowing for better regulation of both temperature and humidity to enhance thermal comfort within hospital environments

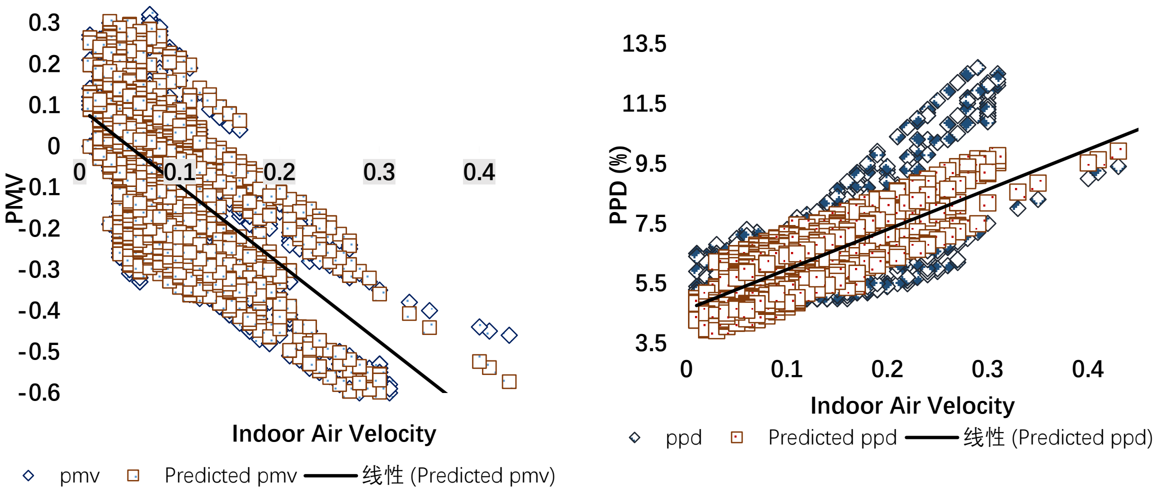


(a) **(b)**

Figure 8. Linear regression predictive analysis, PMV vs Ambient temperature (**a**), and Relative humidity (**b**).

The predicted PMV levels attained through the linear regression model, in conjunction with indoor air velocity parameters, align with the initial estimation of PMV's correlation with indoor operating temperature and relative humidity. As illustrated in Figure 9a, PMV levels follow a negative trend, decreasing from −0.1 to −0.7 as indoor air velocity increases. This trend reflects the enhanced throttling of indoor air supply within the hospital's HVAC duct system at higher velocities, which causes a drop in indoor air temperature and results in overcooling. This is confirmed by highly negative PMV ranges (−0.5 to −0.6) observed at maximum indoor air velocity levels (0.3 to 0.5 m/s). The system's inability to regulate air temperature effectively under high velocity conditions highlights a design limitation that aggravates thermal discomfort for occupants.

Conversely, as indoor air velocity decreases below 0.1 m/s, the predictive analysis indicates system exhibiting slight undercooling/overcooling within nominal PMV ranges of −0.3 to +0.3. However, an increase beyond 0.2 m/s consistently results in undercooling, with PMV values reaching as low as -0.6. Figure 9b shows that patient dissatisfaction, as indicated by PPD levels, intensifies with increasing indoor air velocity. Within the 0.1 to 0.2 m/s velocity range, PPD levels remain between 5.5–7.5%, suggesting a relatively low proportion of dissatisfied occupants. However, at velocities exceeding 0.3 m/s, dissatisfaction rises significantly, with PPD levels reaching their peak at 11%. This increase reflects the direct impact of overcooling caused by excessive air velocity, emphasizing the need for improved air velocity control within the HVAC system to mitigate patient discomfort.



(a) **(b)**

Figure 9. Linear regression predictive analysis, Indoor Air Velocity vs. PMV vs. (**a**), and PPD (**b**).

5. Conclusion

The research demonstrates the applicability of an adaptive thermal comfort regression model in evaluating thermal comfort conditions in the PAF Hospital, Islamabad, under hot and humid climate conditions. The analysis of indoor environmental parameters, coupled with thermal preference and sensation surveys conducted within the in-patient medical wards, identified optimal thermal comfort ranges: indoor temperatures of 22.0–23.0 °C, relative humidity levels between 50–55%, and air velocities from 0.1–0.2 m/s. These conditions were found to enhance the PMV index and reduce PPD levels, ensuring improved occupant satisfaction. The study employed a predictive linear regression model and validated the PMV index using the CBE Thermal Comfort Tool, providing a robust framework for estimating adaptive PMV indices and optimizing indoor thermal conditions.

Despite its contributions, the study is limited by the assumption of utilizing nominal CLO ranges for hospital occupants, which may not account for variations in clothing insulation among different patients. Future research should incorporate dynamic CLO variations to improve the precision of comfort predictions. Additionally, the absence of a dedicated dehumidification system in the hospital HVAC setup emerged as a key factor affecting overcooling and undercooling, as indicated by the correlation between PMV, PPD, and relative humidity. It is recommended that adaptive HVAC systems be implemented, with integrated humidity control mechanisms to mitigate these effects.

To further enhance the utility of this research, future studies should investigate seasonal variations, incorporate larger and more diverse patient populations, and explore advanced Machine Learning (ML) and Deep Learning (DL) models for predictive thermal comfort analysis. Such efforts would help develop more comprehensive guidelines for Hospital HVAC systems, ensuring optimal thermal comfort across diverse climates and patient demographics.

Conflict of Interest Statement

The authors have no competing interests to declare.

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