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Research Article

Keywords: Thermal discomfort, PM_{2.5}, traffic noise, multipollutant exposure, explainable machine learning, Dhaka, public health

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10487427/v1>

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Additional Declarations: No competing interests reported.

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[This research received no external funding]

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Abstract

Rapidly growing megacities in urban areas have road users that experience multiple stressors of heat, air pollution, and noise. In this study, we explore thermal discomfort due to multipollutant exposure in the main roadways of Dhaka, Bangladesh, during monsoon seasons using explainable machine learning framework. Thermal sensation votes were measured in the field along with the corresponding PM_{2.5} concentrations and noise levels measured at the roadsides. Results indicated high thermal discomfort burden and 99.46% of the observations were classified as hot, warm or slightly warm. High concentration of PM_{2.5} (58.35µg/m³) and high noise level (82.96dB) were found during the mean monsoon, which showed high co-exposure. The discrimination (AUC) of the machine learning models trained using multipollutant and microclimatic predictors was good (AUC = 0.96). Explainable modelling determined the relative contribution of heat, particulate matter and noise to predicted discomfort. The results revealed that the major roads of Dhaka have a combined environmental health impact, which is further increased by the synergy between thermal stress and fine particulate pollution along with traffic noise. The findings highlight the importance of addressing roadside heat, air quality and noise all at once in densely populated tropical urban areas.

Keywords: Thermal discomfort; PM_{2.5}; traffic noise; multipollutant exposure; explainable machine learning; Dhaka; public health.

1. Introduction

In rapidly developing megacities, urban roadway environments are one of the most complex and least evaluated exposure environments. In Dhaka, the pedestrians, commuters, traffic police, street vendors, rickshaw pullers and other outdoor road users are subjected to multiple environmental stressors due to the combination of intense traffic activity, high population density and road side commercial activities, which are lacking street level ventilation [1]. Some of these stressors are fine and coarse particulate matter, traffic related noise, increased carbon dioxide, heat, humidity, horn intensity, fuel odor and exposure conditions due to congestion [1-2]. In the in-situ roadway microenvironments, such factors are seldom found individually; rather, they are integrated into a multipollutant and multisensory exposure pattern that can impact the environment and human physiology. The exposure burden from a single pollutant will therefore give only a partial picture, especially in urban areas like Dhaka, where the distribution of pollution sources and exposure are highly unevenly distributed along major road corridors [3].

Thermal comfort in an outdoor roadway environment is becoming more important for public health as it not only considers subjective comfort, but also potential susceptibility to environmental stress. Fatigue, headache, heat stress, discomfort of the respiratory system, decreased mobility outdoors, loss of productivity, and changes in walking or commuting habits are attributed to prolonged exposure to heat, humidity, polluted air, traffic noise and congestion [4]. These effects can be more intense for those who work for a longer duration in the vicinity of road space users, such as those who earn low wages, traffic management workers, non-

motorized transport users, and informal vendors [4-5]. In this sense, perceived thermal comfort can be used as one of the indicators of human perception of his daily life environmental exposures. Combining perception-based measures like air-quality perception, common health complaints, headache occurrence, clothing level, horn intensity, fuel smell, and ASHRAE-based thermal comfort response with measured pollutants (PM_{2.5}, PM₁, PM₁₀, CO₂, noise level, temperature, and humidity) can offer a more holistic picture of the public health risk associated with roadway exposure [5].

The study of urban air pollution, traffic noise, heat stress and outdoor thermal comfort has been studied in individual fields, but not as an integrated exposure system [1-3,6-7]. Limited evidences exist in the context of Dhaka for the interaction of PM, noise, CO₂, temperature, humidity, traffic density, weather conditions, perceived air quality, health complaints, horn exposure and fuel smell on the perceived thermal comfort/discomfort along the main roads of the city [6-7]. In addition, traditional statistical methods might not be able to respond to the interactions and non-linearities between multipollutant exposures and human comfort perception. Machine learning models provide a potential avenue to enhance prediction accuracy in complex environmental health datasets, but application of this approach needs to be accompanied by interpretability to enable scientific and policy relevance. Explainable AI techniques, such as SHAP analysis, can be used to provide a better understanding of the relative impact and direction of influence of the most important exposure variables and make predictive modelling more of an interpretable public health assessment tool [8-9].

This study places roadway thermal discomfort as a potentially predictable outcome of multipollutant exposure to public health in Dhaka. The specific objectives are to evaluate spatial variation of multipollutant exposure along selected major roadways in Dhaka to have an idea of thermal exposure, to predict thermal comfort/discomfort based on ASHRAE using

Decision Tree, Random Forest and XGBoost models, to compare the performance of the models using the ROC-AUC, indicators derived from confusion matrix, sensitivity, specificity, accuracy, precision, recall, F1-score, and other evaluation metrics etc., to explain the most important predictors of thermal discomfort using SHAP analysis, and to identify the exposure conditions with public health relevance using sensitivity analysis [2,10-11]. The variables that are taken into account in this study are PM_{2.5}, PM₁, PM₁₀, CO₂, noise, humidity, temperature, traffic density, common health complaints, public perception of air quality, weather observation, headache report, clothing level, horn intensity, and fuel smell, with the ASHRAE-based thermal comfort category serving as the target variable [12-14]. The study provides an inclusive and policy-relevant framework for the human-centered assessment of environmental health risk in Dhaka's roadway microenvironments by combining exposure monitoring in the field, perception-based health and comfort responses, machine learning prediction, and explainable AI.

2. Methods Section

2.1 Study Area

This study was done on major roadway corridors of Dhaka, Bangladesh to explore the thermal discomfort due to multipollutant roadside exposure. Dhaka has been chosen as one of the traffic congested and dense population cities in South Asia. The Population and Housing Census 2022 shows that the population of Dhaka North City Corporation is 5,990,723 (density 30,531 persons km⁻²) and Dhaka South City Corporation is 4,305,063 (density ≈39,406 persons km⁻²) [15]. This extreme population density increases the amount of time pedestrians, commuters,

drivers, street vendors, traffic police, and informal-sector workers spend near vehicles, road dust, heat, humidity, and traffic noise, leading to increased exposure to these factors [16-20].

Average Air Quality measures are taken by considering the average of PM_{2.5} concentration over the last three months. Average Air Quality is computed by calculating the average of PM_{2.5} concentration in the past three months (2024) [21] and is regarded as extremely poor air quality if it exceeds the recommended level of the WHO annual guideline which is 5 µg m⁻³. Roadside studies have even higher concentrations, with a maximum concentration of PM_{2.5} of 172.2 µg m⁻³ in Mirpur-10 in mixed and motorized traffic zones [21]. The above conditions justify the use of roadside locations with high traffic exposure to evaluate thermal discomfort in exposure to multiple pollutants [22-25].

The sites were chosen purposively, where the amount of traffic was high, the commuters were moving constantly, there was mixed land use and transport hub, there were metro stations, commercial activity, the pedestrians are crowding in the neighbourhood and there is activity around the roadsides. The following locations were selected: Abdullahpur, West Jatrabari Road, North Jatrabari, South Jatrabari, Jatrabari Thana, Sayedabad Railgate, Sayedabad Road, Kawran Bazar, Farmgate, Bijoy Sarani, Khamar Bari, Airport Road, Metro-Uttara, Uttara-Uttar Metro, Kamarpara, Mirpur 10 and Dhanmondi. The spatial representation was made by grouping of sites into three major corridors: northern corridor (Abdullahpur, Airport Road, Metro Uttara, Uttara-Uttar Metro, Kamarpara); the central corridor (Kawran Bazar, Farmgate, Bijoy Sarani, Khamar Bari); and southern corridor (West Jatrabari Road, North Jatrabari, South Jatrabari, Jatrabari Thana, Sayedabad Railgate, Sayedabad Road). To add to the list, Metro Mirpur 10 was considered as an extra high exposure metro-connected urban node [26-27]. The field data were taken during the late monsoon (20 August 2025 to 15 October 2025), post-monsoon (15 October 2025 to 15 January 2026) and winter transition period (15 January 2026

to 31 January 2026). Table 1 shows the information of the roadways monitoring sites selected for the study in Dhaka corridor with their geographic coordinate and strategic reason. This seasonal coverage is critical as temperatures, relative humidity, wind condition and pollutant concentration may change significantly during these time periods. This meant that the chosen sampling time period enabled the study to encompass both meteorological and pollution related variability in real roadside conditions.

Temporal variation in the traffic, exposure to pollutants and thermal discomfort was measured at three time windows during the day. The morning peak period was defined as 07:00–10:00, the afternoon period as 12:00–15:00, and the evening peak period as 17:00–20:00. In order to capture high traffic congestion and commuter traffic, as well as the higher heat exposure and potential thermal discomfort in the afternoon, morning and evening traffic periods were added.

Table 1: Selected roadway monitoring locations in Dhaka

Corridor	Monitoring location	Latitude	Longitude	Site relevance
Northern corridor	Abdullahpur	23.752890	90.394857	Northern traffic entry point and commuter zone
Northern corridor	Airport Road	23.877738	90.360213	Airport-bound mixed traffic and high vehicle flow
Northern corridor	Metro Uttara-Central	23.709033	90.428080	Metro-linked commuter exposure location

Northern corridor	Metro Uttara	23.859665	90.364892	Metro-linked roadside commuter zone
Northern corridor	Metro Uttara-Uttar	23.880097	90.401118	Transit-related roadside exposure point
Northern corridor	Kamarpara	23.891254*	90.388537	Northern urban expansion and commuter movement
Central corridor	Kawran Bazar	23.750458	90.393151	Commercial activity, pedestrian flow, and traffic congestion
Central corridor	Farmgate	23.852109	90.407445	Major commuter and public transport zone
Central corridor	Bijoy Sarani	23.711446	90.429505	Administrative and traffic corridor
Central corridor	Khamar Bari	23.758953	90.384028	Institutional and roadside exposure area
Southern corridor	West Jatrabari Road	23.765064	90.386136	Congested mixed-traffic roadway
Southern corridor	North Jatrabari	23.710751	90.435084	Southern transport gateway
Southern corridor	South Jatrabari	23.759062	90.384100	High roadside movement and traffic exposure

Southern corridor	Jatrabari Thana	23.758640	90.389846	Dense roadside activity and transport movement
Southern corridor	Sayedabad Railgate	23.709387	90.434687	Railgate-related congestion and vehicle queuing
Southern corridor	Sayedabad Road	23.710450	90.435546	Bus, truck, and public transport exposure corridor

All locations can be spatially located using **table 1**, which lists, for each station, the exact latitude and longitude. One thousand, one hundred and nine observations were taken from the roadside at the various sites. Observations were only individuals whose exposure conditions regarding multipollutant and meteorology were unique to the observation site, on which thermal discomfort was predicted by explainable machine learning. The sampling therefore took into account both spatial variability, between the main roadway corridors of Dhaka city, and temporal variability, between the traffic and heat exposure hours in the day. This design offers a solid empirical footprint for evaluating the effects of a dual exposure to traffic-related pollution and microclimatic stress on thermal discomfort in highly exposed urban roadway environments.

Fig 1. Shows the spatial distribution of the roadway monitoring locations selected in the Dhaka metropolitan area with the administrative boundary of Dhaka highlighted in red. The monitoring network covers strategic high traffic transport corridors, intersections and mass transit facilities that can be subject to intense environmental stress. Comprehensive geospatial configuration ensures representative sampling of diverse urban microclimates, vehicular density profiles and pedestrian exposure scenario necessary for modeling multipollutant dynamics and thermal discomfort throughout the city (**fig 1.**).

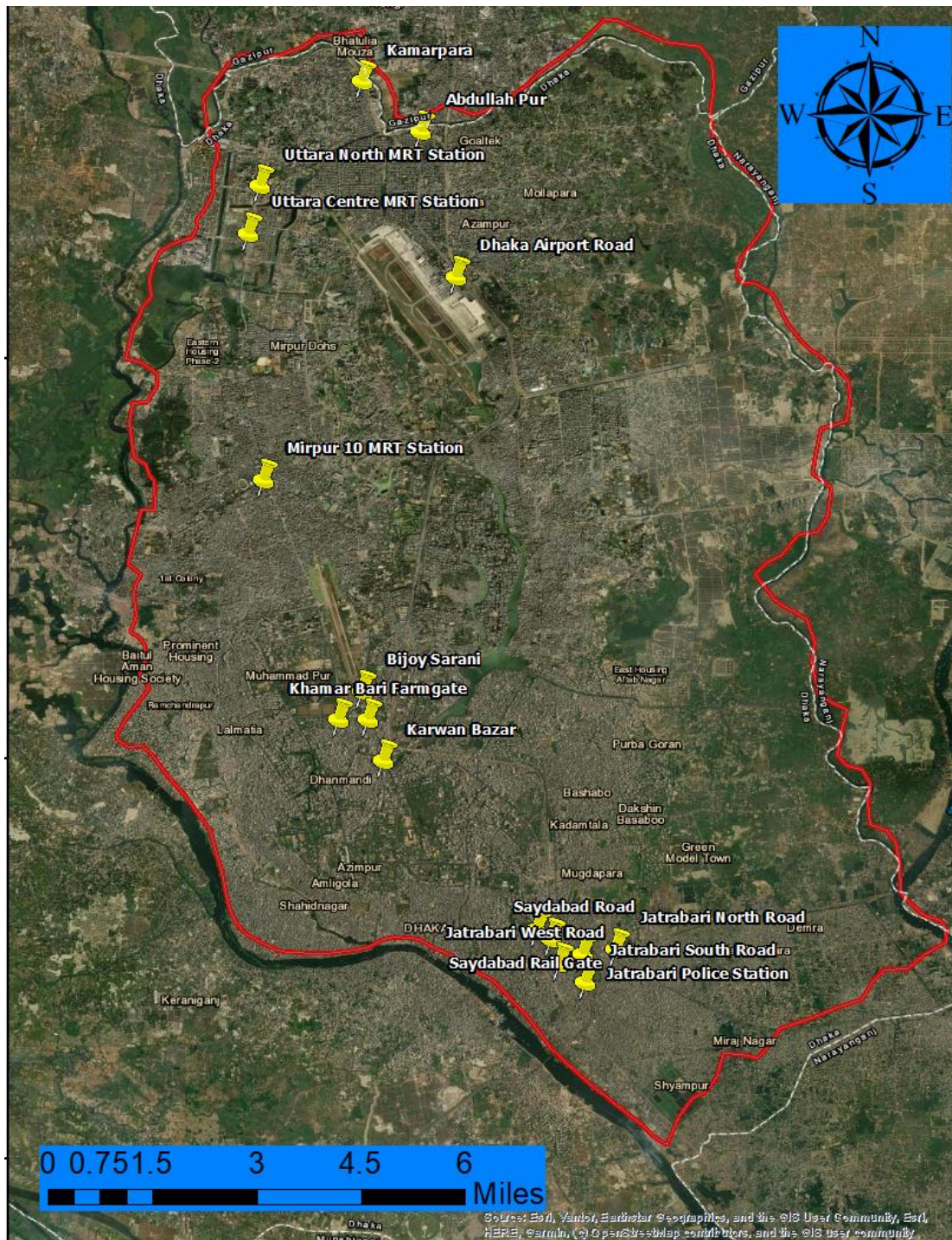


Fig 1: Selected roadway monitoring locations map.

2.2 Study Design and Data Collection

A cross sectional field based observational study was conducted to evaluate thermal discomfort due to multipollutant exposure on different roadway corridors of Dhaka city. The design allowed for the simultaneous measuring of conditions of environmental exposure and participant-level thermal comfort responses at specific sampling locations and time periods [28-31]. Calibrated field instruments were used to obtain environmental data. The air quality and micro-environmental conditions in the vicinity of the road were measured by an intelligent air detector (JLDC) and traffic noise levels were recorded by a mini sound level meter (UT353) [32-34]. To reduce the measurement errors, deployment of sensors was preceded by checking and calibration following the manufacturer's procedures. Observations were made at a number of GPS-referenced sampling points in each of the selected corridors, which enabled the precise location of each observation on the roadway (Table 1).

Demographic characteristics, exposure context, perceived heat stress, thermal discomfort and associated health symptoms were assessed through a structured interview survey that was administered simultaneously. The participants' subjective responses were measured at the same time as the environment, allowing them to link the subjective response to the true pollutant, noise, and thermal data. After field collection, sensor and survey data was quality checked for the presence of missing, incorrect, duplicate, and outlier data. Cleaned data was merged by the sampling location, sampling time and participant identifier. Feature engineering was done to create exposure, roadway, and participant-level predictors that could be used for machine learning analysis. Standard classification criteria were used for developing and testing predictive models of thermal discomfort. SHAP was used for interpretation of the contribution of each exposure variable and sensitivity analysis was performed to evaluate the impact of key predictors on the model outputs.

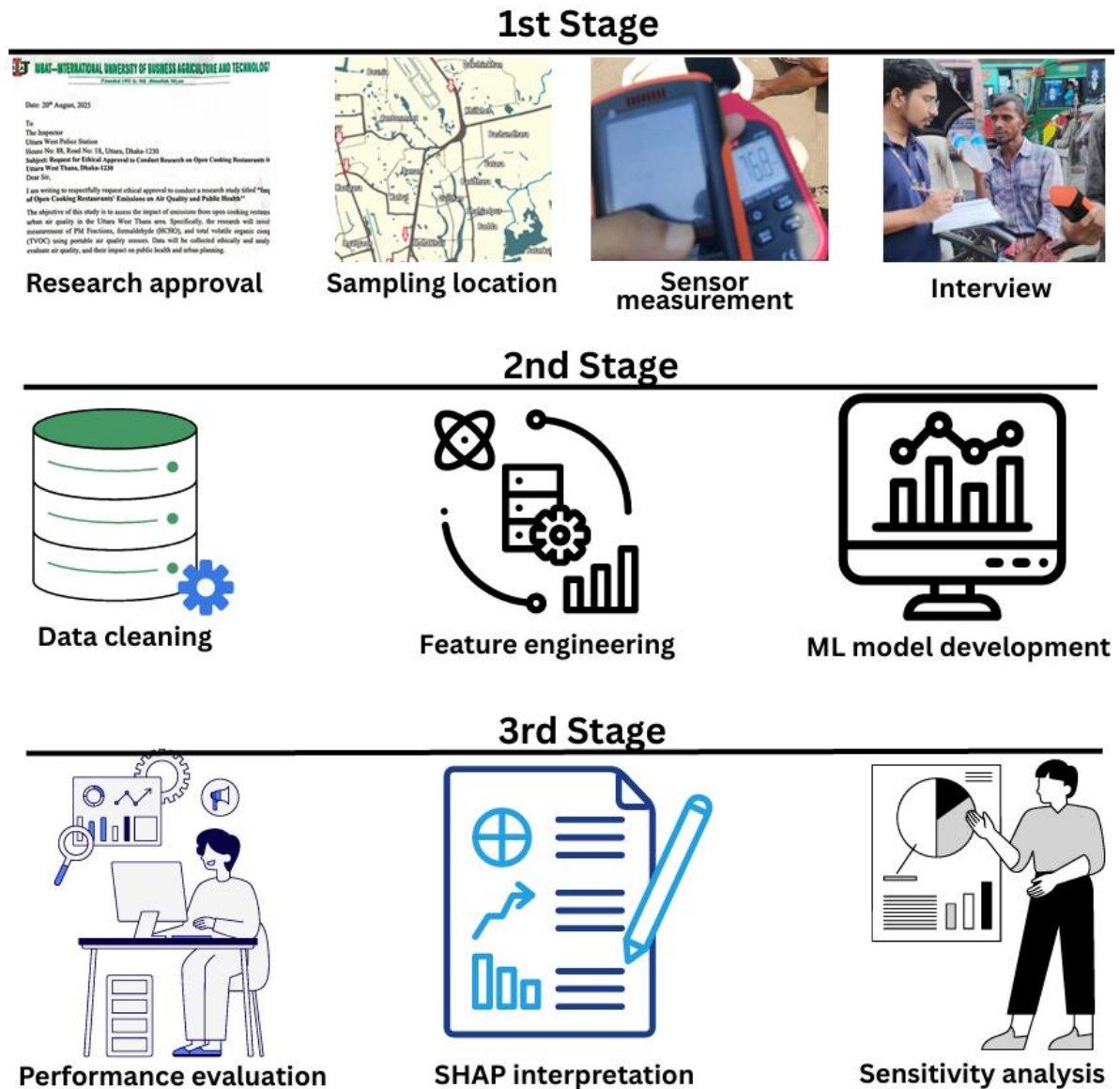


Fig 2: Workflow of study design.

The detailed steps of this study are shown in **Fig. 2**, where a systematic sequence from data acquisition to high interpretability of the models is demonstrated. The process started by obtaining approval for the fundamental research, and then the strategic selection of sampling sites and the collection of real-time environmental data by using sensor measurements. Interviews were held to gain qualitative data in relation to public health and thermal perception so that human-centric data could be incorporated.

The next computational step was to meticulously clean the data and engineer the features for high fidelity analysis. These features were then adopted for ML model development, with machine learning algorithms being developed to identify patterns between the thermal discomfort and the exposure to pollutants. Model validation and transparency were the last phase of the study, in which the model's accuracy was evaluated, the individual pollutant contribution to the results was explained using the SHAP method, and the results were tested for their robustness under different environmental conditions by performing a sensitivity analysis.

2.3 Data Preprocessing

All field observations were preprocessed before development of models to make data consistent, reliable in measurements and reproducible in analysis [35-36]. The raw data included sensor-derived environmental data, noise measurements, GPS data providing roadway information and subjective thermal comfort reports collected from participants. All records were reviewed for missing data, logical consistency, and for possible measurement errors.

The missing values were analyzed for each of the variables [37-38]. Records that did not include the thermal comfort outcome or that did not identify a high risk/low risk class were not included. Numerical variables with missing data were imputed using strong central tendency methods, and categorical variables with missing data were imputed with the most common and valid answer. Variables with too many missing items were only removed when it would affect the reliability of the model.

Descriptive statistics, boxplots and instrument-specific physical ranges [39] were used to identify outliers in each of the numerical variables (concentrations of pollutants, temperature-based variables, humidity and noise). Only those values that were clearly the result of a sensor malfunction, a reset, a recording error, or from impossible range measurements were deleted; the extreme values that were retained were considered as plausible high roadside exposures.

Errors include unstable start-up readings, duplicate readings, missing GPS and time readings, abnormal readings of zero, and readings beyond the range of the air detector, which are removed before feature engineering [39-40]. Where necessary according to the distance-sensitive algorithms such as logistic regression, support vector machine and k-nearest neighbours, the continuous predictors were scaled following the same pipeline used for the tree-based ones for consistency [41] [42]. Categorical variables were coded and engineered features were created from exposure, roadway, temporal and participant-level data. The information leakage has been prevented by the assessment and treatment of class imbalance within the training set [39-42]. The data was cleaned and then split into two sets: a training set and a test set, with the split being stratified and cross-validation being performed on the training set. The preprocessing (imputation, scaling, encoding and balancing) was limited to the training workflow.

A brief description of the quality assurance process is given in Table 2. After discarding 12 observations for key predictors and 20 observations for the lack of the thermal comfort outcome, 37 observations with sensor errors and 7 observations that were duplicate or that included inconsistent GPS/time information were discarded. A final dataset of 1,109 observations was obtained after verification of outliers which identified verified measurement errors (VMEs) and eliminated them leaving the extreme exposures.

Table 2. Data cleaning summary.

Data preprocessing step	Cleaning criterion	Observations removed	Remaining observations
Initial raw dataset	Total field observations collected	[0]	[1,200]
Missing outcome removal	Records without thermal comfort response or discomfort class	[20]	[1180]
Missing predictor treatment	Records with unavailable key exposure variables after imputation review	[12]	[1168]
Sensor error removal	Device reset values, unstable start-up readings, impossible values, abnormal zero values	[37]	[1131]
Duplicate/inconsistent record removal	Duplicate entries, mismatched GPS/time records, survey-sensor mismatch	[7]	[1124]
Outlier verification	Confirmed measurement or entry errors removed; valid extreme exposure values retained	[15]	[1109]
Final modelling dataset	Cleaned observations used for machine learning analysis	—	[1109]

Table 2. Summary of data preprocessing and cleaning steps applied to the field-based

environmental exposure and thermal discomfort dataset before machine learning model development.

2.4 Machine Learning Model and Analysis

Multipollutant and microclimatic exposures have been translated to thermal discomfort at the participant level using machine learning models for primary corridors in Dhaka. Thermal discomfort has been predicted at the participant level for main roadway corridors in Dhaka, based on multi pollutant and microclimatic exposures, using machine learning models. Data from the modelling dataset combined the structured interview data with sensor-based environmental data from 1,109 participants. Particulate matter indicators, traffic-related noise, CO₂ concentration, and heat-stress related environmental variables were used as predictor variables [43]. The thermal comfort status was extracted from the participants' reports and assigned to comfort/discomfort and risk-based categories, respectively.

Three supervised algorithms were used: Decision Tree (DT), Random Forest (RF) and Extreme Gradient Boosting (XGBoost). The models were chosen for their capability to model the non-linear relationships and interactions between air pollution, noise, heat stress, and responses of individuals [44]. Decision Tree was used as an interpretable baseline classifier [44]. Averaging of predictions using Random Forest was used to increase the level of stability in the predictions and to decrease the overfitting [45] problem. XGBoost was added due to its success with tabular data and ability to model complex exposure–response relationships [45]. The model architecture and hyperparameter settings are briefly summarized in **Table 3**.

Table 3: Model description and key hyperparameters

Model	Main purpose	Key hyperparameters
Decision Tree	Used as a simple baseline model for predicting thermal discomfort. It gives easy-to-understand decision rules.	max_depth, min_samples_split, min_samples_leaf, criterion
Random Forest	Used to improve prediction accuracy by combining many decision trees and reducing overfitting.	n_estimators, max_depth, max_features, min_samples_split
XGBoost	Used as an advanced model to capture complex relationships among pollution, thermal, traffic, and human factors.	n_estimators, learning_rate, max_depth, subsample, colsample_bytree

The dataset was split into a train and test set (stratified) to maintain the class distribution. The training set was used for cross validation, and hyperparameter tuning was limited to tuning in the training workflow. The area under the receiver operating characteristic curve (ROC-AUC) was the main metric used to evaluate model performance, with accuracy, sensitivity, specificity, precision, recall, and F1-score metrics used when applicable. SHAP analysis was used to measure the influence of each predictor on the thermal discomfort prediction, and to identify the most important exposure variables [47-48]. To further explore the impact of the key multipollutant and heat-stress variables, sensitivity analysis was then performed to assess the influence of changes in these variables on discomfort risk prediction [47-48]. This framework not only gave predictive information, but also interpretable information on the environmental factors that influence thermal discomfort in roadside environments.

3. Results

The descriptive features of the roadway exposure data, the distribution of thermal comfort responses, spatial exposure patterns, and the performance of the machine learning models developed for thermal comfort classification are presented. In addition to the results, there is correlation analysis, evaluation of the ROC curve, interpretation of the confusion matrix, explain ability through SHAP, and sensitivity analysis.

3.1 Participant and Exposure Characteristics.

This section briefly presents the socio-demographic profile of the study population, their roadway exposure pattern, and their thermal comfort perceived status. 1,109 persons were interviewed in major roadway environments of Dhaka to get a glimpse of how exposure to traffic-related multipollutant might affect the thermal comfort of people in the outdoors. Participant characteristics were age, gender, occupation, exposure duration and perceived thermal comfort class. These variables were chosen as they may vary between individuals depending on demographic characteristics, kind of outdoor activity and time spent in proximity to busy streets and roads in order to account for the individual vulnerability to heat stress related to air pollution exposure.

Thermal comfort perception was documented from the interview responses according to the ASHRAE thermal sensation guideline [49] which includes the comfort classes: Hot (H), Warm (W), Slightly Warm (SW), Comfortable/Neutral (C), Slightly Cool (SC), Cool (C), and Very Cool (VC). This classification was useful for reflecting the subjective thermal experience of the participants in the real roadway conditions. The major roads of Dhaka are usually heavily trafficked, have high air temperature and also a high concentration of pollutants, hence the participant level and exposure related variables give a baseline understanding of thermal

discomfort in subsequent sections of the report, where the machine learning is used to predict thermal discomfort [49-50]. A summary of the distribution of the study participants by thermal comfort classes is shown in **Table 4**. Of the people surveyed (N = 1109), most reported high thermal discomfort in the major roads of Dhaka. Class "H" made up the largest percentage of the sample (n = 552, 49.8%) followed by class "W" (n = 499, 45.0%). Class "SW" accounted for a smaller percentage of the population at 4.6% (n = 51). In contrast, classes indicating cooler or neutral sensations—namely "SC" (0.3%, n = 3), "C" (0.2%, n = 2), "VC" (0.1%, n = 1), and "N" (0.1%, n = 1)—were minimally represented in the dataset. The results here suggest a strong bias in the respondents' responses in the higher thermal sensation categories during multi-pollutant exposure events.

Table 4: Participant thermal comfort class.

Thermal comfort class	respondent	Percentage
H	552	(49.8%)
W	499	(45.0%)
SW	51	(4.6%)
SC	3	(0.3%)
C	2	(0.2%)
VC	1	(0.1%)
N	1	(0.1%)

In general, the results suggest that most of the subjects experienced a significant amount of thermal discomfort, which is a typical experience along the main roadways in Dhaka during high heat exposure.

Demographic and environmental exposure data were gathered to estimate exposure to multiple pollutants on thermal discomfort. Fine particulate matter (PM), noise levels, carbon dioxide (CO₂) concentrations, ambient temperature and relative humidity were measured. These parameters reflected the overall exposure of the participants and included both air quality and microclimatic parameters that are important for thermal perception and public health impacts [51].

Table 5. shows the descriptive statistics of the environmental and meteorological metrics that were measured during the study. The particulate matter levels exhibited a high polluted situation on the key highways of Dhaka, the mean concentration of which was $81.14 \pm 19.28 \mu\text{g}/\text{m}^3$ for PM₁₀, $71.37 \pm 16.42 \mu\text{g}/\text{m}^3$ for PM_{2.5}, and $58.35 \pm 14.73 \mu\text{g}/\text{m}^3$ for PM₁. The same is true for exposure to gaseous and acoustic pollution, as evidenced by the carbon dioxide (CO₂) concentration, which averaged $798.69 \pm 131.69 \text{ ppm}$ (up to 1105.00 ppm), and the noise level, which reached a maximum of $82.96 \pm 7.09 \text{ dB}$. The mean ambient temperature was found to be $32.94 \pm 0.85^\circ\text{C}$, ranging up to 37.00°C while mean ambient relative humidity was $60.92 \pm 2.84\%$. These metrics highlight the very challenging ambient conditions and offer an important baseline for assessing the cumulative impacts of multipollutants and thermal stress on public health.

Table 5: Environmental exposure summary.

Variable	Mean	SD	Min	Max
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PM2.5 ($\mu\text{g}/\text{m}^3$)	71.37	16.42	23.00	100.00
PM1 ($\mu\text{g}/\text{m}^3$)	58.35	14.73	12.00	85.00
PM10 ($\mu\text{g}/\text{m}^3$)	81.14	19.28	27.00	115.00
CO ₂ (ppm)	798.69	131.69	414.00	1105.00
Noise level (dB)	82.96	7.09	59.00	103.00
Relative humidity (%)	60.92	2.84	52.00	70.00
Temperature ($^{\circ}\text{C}$)	32.94	0.85	31.00	37.00

The results overall suggest that subjects were exposed to a combination of high levels of particulate matter, high noise and warm humid conditions, which could lead to higher levels of thermal discomfort in roadway environments.

3.2 Spatial Distribution of Exposure and Thermal Discomfort.

Spatial variation of environmental exposure and perceived thermal discomfort around major roadways in Dhaka is explored in this section. Pollutant exposure and thermal stress will not

be the same for all road segments in the study area, due to the differences in traffic intensity, built-up density, road-side ventilation, surface materials and human activity patterns. Thus, particulate matter, noise, CO₂, temperature, humidity and thermal comfort classes mapping will provide useful information regarding the location specific exposure burden [52].

The correlation heat map shows the general pattern of spatially related exposure and thermal discomfort related indicators in the major roadway environments of Dhaka (fig 3.). The relationship between the variables of particulate matter was strong and positive between PM_{2.5} and PM₁ ($r = 0.68$), PM₁ and PM₁₀ ($r = 0.65$), and PM_{2.5} and PM₁₀ ($r = 0.50$), with fine and coarse particulate matter generally increasing with one another for all locations exposed to roadway construction. This implies a common source of emissions associated with traffic or the roadside. CO₂ also had significant positive associations with public perception of poor air quality ($r = 0.57$), headache symptoms ($r = 0.62$) and reported health complaints ($r = 0.37$), highlighting the relevance of CO₂ as a measure of accumulation of exposure in road traffic environments.

The direct relationships between thermal comfort and individual pollutants and meteorological variables were found to be comparatively weak, such as CO₂ ($r = 0.18$), public perception of air quality ($r = 0.13$), and horn exposure ($r = 0.12$). This weak linear association indicates that thermal discomfort perception in roadway environments might not be only related to one single exposure factor, but rather be influenced by all the factors mentioned along with individual perception. Thus, there is a need for an explainable machine learning approach, because the complexity and non-linearity of exposure interaction effects may give better understanding of the spatial variation in thermal discomfort than simple pairwise correlations (**fig 3.**).

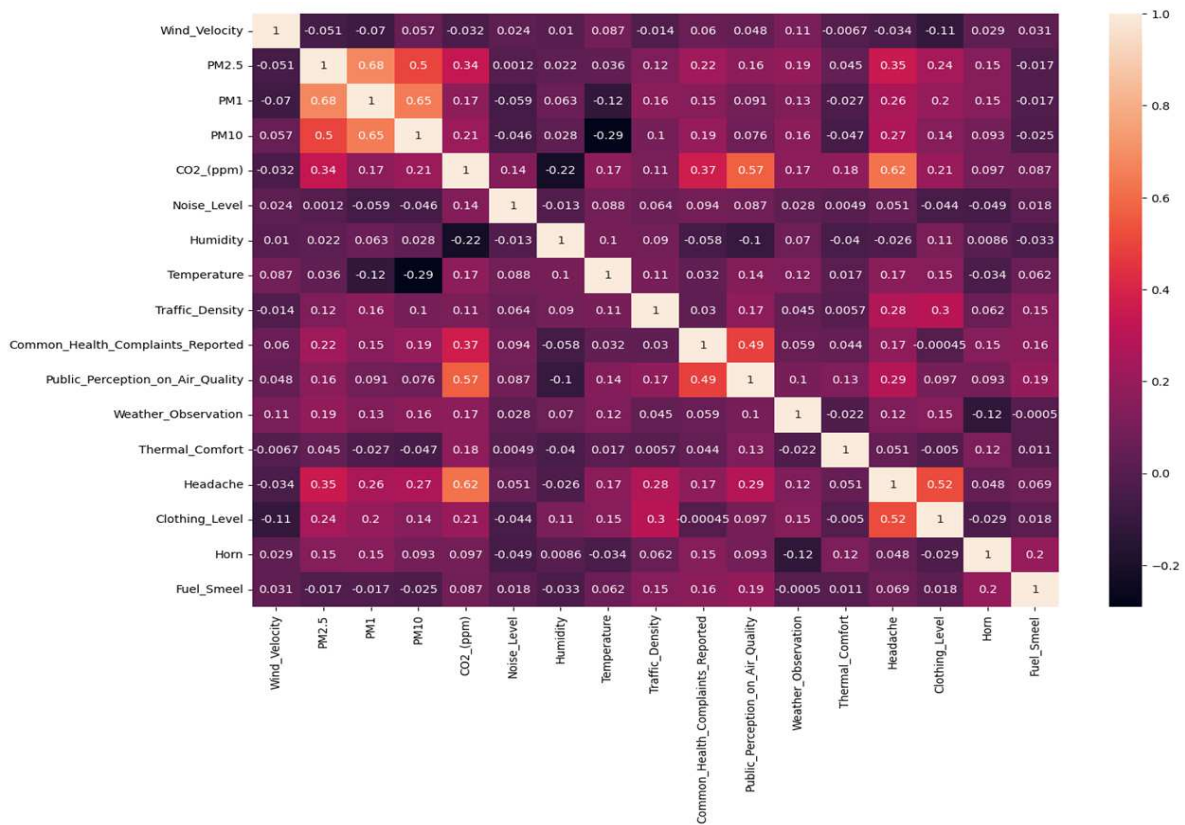


Figure 3: Correlation heatmap of multipollutant exposure and thermal discomfort-related variables in Dhaka roadway environments.

The spatial assessment will help to determine areas of the roadway that had the greatest environmental stress and thermal discomfort. This is especially true for Dhaka, given the high volume of road traffic, lack of green spaces, and heat-accumulation of urban surfaces, which can worsen outdoor discomfort. This section connects measured exposures to reported thermal comfort responses, providing a geographic context to understanding exposure hotspots and for the subsequent explainable machine learning analysis for predicting thermal discomfort risk.

3.4 Model Performance Comparison

For predictive performance of machine learning models for thermal discomfort under multipollutant exposure, the performance of Decision Tree, Random Forest and the XGBoost models are compared. Each model was evaluated for its discrimination ability with the use of Receiver Operating Characteristic (ROC) curves. The comparison helped identify the best and most stable model to describe the complex interactions between environmental variables and to predict individual thermal discomfort response in real-world roadway settings, as suggested by the researchers [53].

Fig 3. shows the Receiver Operating Characteristic (ROC) curves of Decision Tree (DT), Random Forest (RF) and XGBoost models for their discriminative performance in predicting thermal discomfort under multipollutant exposure. The predictive power of Decision Tree model was ranged between moderate and good levels (AUC from 0.50 to 1.00) for different classes, which has some classification power variation. In contrast, the Random Forest model and XGBoost models showed high performance with most classes' AUC ranging from 0.97 to 1.00, indicating high robustness of the model and good separation between classes. Interestingly, XGBoost performed slightly better in minority classes with perfect classification (AUC = 1.00) for several of them.

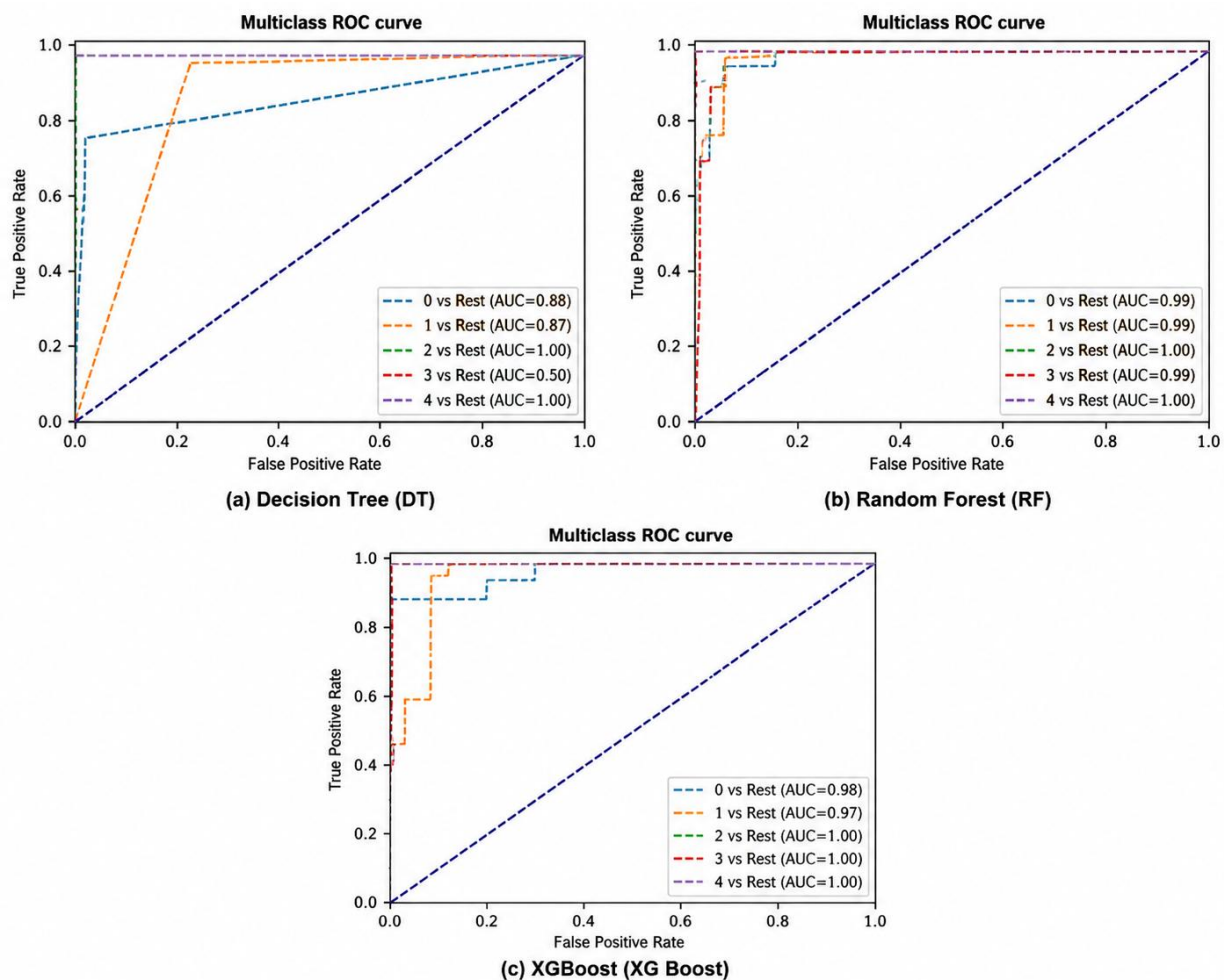


Figure 3: ROC curves for (a) Decision Tree, (b) Random Forest, and (c) XGBoost

The results of these (**fig. 3.**) analyses indicate that ensemble based models such as XGBoost are superior in capturing the complex and nonlinear relationships between the environmental variables and individual thermal discomfort responses, compared to single Decision Tree models.

The overall performance of the three machine learning models to predict thermal discomfort under multipollutant exposure is summarized in **Table 5**. Random Forest (RF) and XGBoost models outperformed the Decision Tree (DT) model with an accuracy of 0.96, respectively 0.95. The mean squared error (MSE) was similar for all models (0.06), and the root mean squared error (RMSE) was between 0.24 (RF) and 0.25 (DT, XGBoost), signifying that the

models have low deviation from the predictions. Considering the F1-score, RF and XGBoost again outperformed (0.96) with a better balance between precision and recall than DT (0.95).

Table 5: Model performance comparison.

Matrix	Accuracy	MSE	RMSE	F1-score
DT	0.95	0.06	0.25	0.95
RF	0.96	0.06	0.24	0.96
XGBoost	0.96	0.06	0.25	0.96

The results shown here (**table 5.**) indicate the strength and stability of the ensemble-based models, especially RF and XGBoost, for the ability to capture complex, nonlinear relationships between the environmental exposures and predicting the individual thermal discomfort responses.

3.5 Confusion Matrix and Actual vs Predicted Class

Confusion matrices were also produced for every machine learning model to further assess the performance of the models and gain insight into how they classify each individual class. These matrices can be used to report in detail the agreement between the actual thermal discomfort category and the predicted thermal discomfort category, showing patterns of correct, as well as incorrect, classification for a variety of exposure scenarios [54]. The visualization of actual versus predicted classes can be used to determine the strengths and weaknesses of the model in addition to the overall model performance and ROC analysis, and can provide a complementary perspective on model reliability in real world roadway environments [54-55].



Figure 6: Confusion matrices for DT, RF, and XGBoost.

Confusion matrices for the DT, RF, and XGBoost models for the classification of thermal discomfort classes for main roadways in Dhaka due to multipollutant exposure are presented in **Fig. 6**. The values extracted reveal that they are in substantial agreement with the actual classes of thermal discomfort with a majority of observations falling along the diagonal of each matrix. In the case of the XGBoost model, there were 231 slightly cool observations correctly classified, 171 neutral observations, 244 slightly warm ones, 242 warm ones, and 238 hot ones.

Errors were rarely seen, with only 2 Slightly Cool sample predictions being Neutral, 5 Neutral samples being predicted as Slightly Cool, 1 Neutral sample being predicted as Hot, and 1 Slightly Warm sample predicted as Neutral. The overall accuracy of XGBoost is about 99.21% correct out of 1135 observations.

The matrix lists the number of correctly classified observations for the Decision Tree (DT) model: 191 for Slightly Cool, 125 for Neutral, 195 for Slightly Warm, 189 for Warm, and 199 for Hot. Only three samples from the nearby Slightly Cool class were misclassified as Neutral and six samples were misclassified as Slightly Cool from the nearby Neutral class. For the classes of Slightly Warm, Warm, and Hot, no misclassification was noted. DT correctly classified 899 out of 908 observations and the accuracy is around 99.01% based on the matrix shown.

The classification performance of the three models, the Random Forest (RF) model was the most efficient. It correctly classified 232 Slightly Cool, 172 Neutral, 245 Slightly Warm, 242 Warm, and 238 Hot observations. 5 samples were predicted as Neutral and only 1 Slightly Cool sample was predicted. There were no errors detected in the Slightly Warm, Warm and Hot classes. Therefore, the accuracy of RF is about 99.47% (1129/1135). Overall the confusion matrices show that all three models did a very good job of predicting, with RF showing the most consistent results of prediction, followed by XGBoost and DT. The range of errors was generally small with the majority being between the Slightly Cool and Neutral classes indicating that there tended to be closer classification boundaries between these adjacent thermal perception classes.

3.6 SHAP Explainability

To account for the role played by each environmental variable on thermal discomfort prediction, SHapley Additive exPlanations (SHAP) values were added for each of the ensemble models [56]. In SHAP analysis, the model-agnostic approach allows the quantification of the contribution of each feature to the prediction, in this case, the impact of multipollutant exposure on thermal discomfort, including PM, noise, CO₂, temperature and humidity [56]. This explainability framework can be used to identify the most influential predictors, can help with model trustworthiness and can guide recommendations for public health interventions in urban roadway environments.

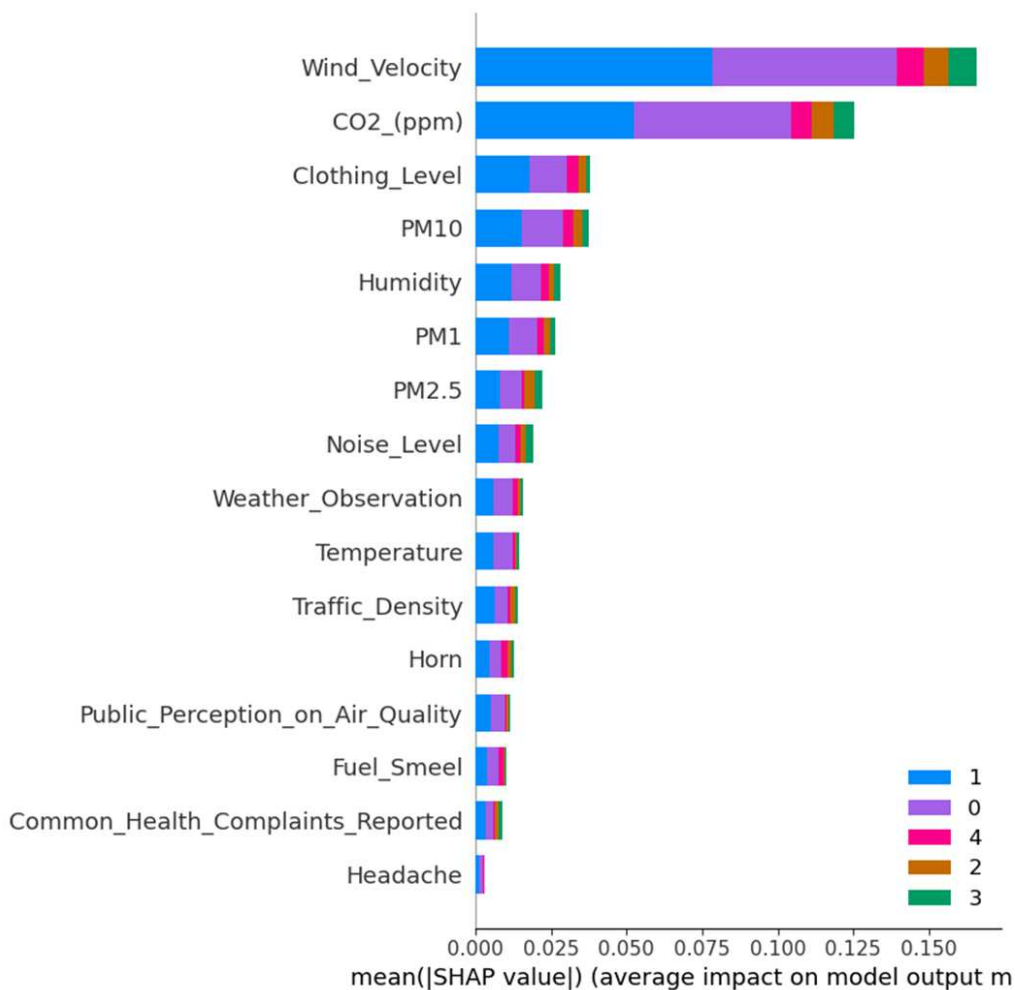


Figure 7: SHAP-based best-performing model, Random Forest.

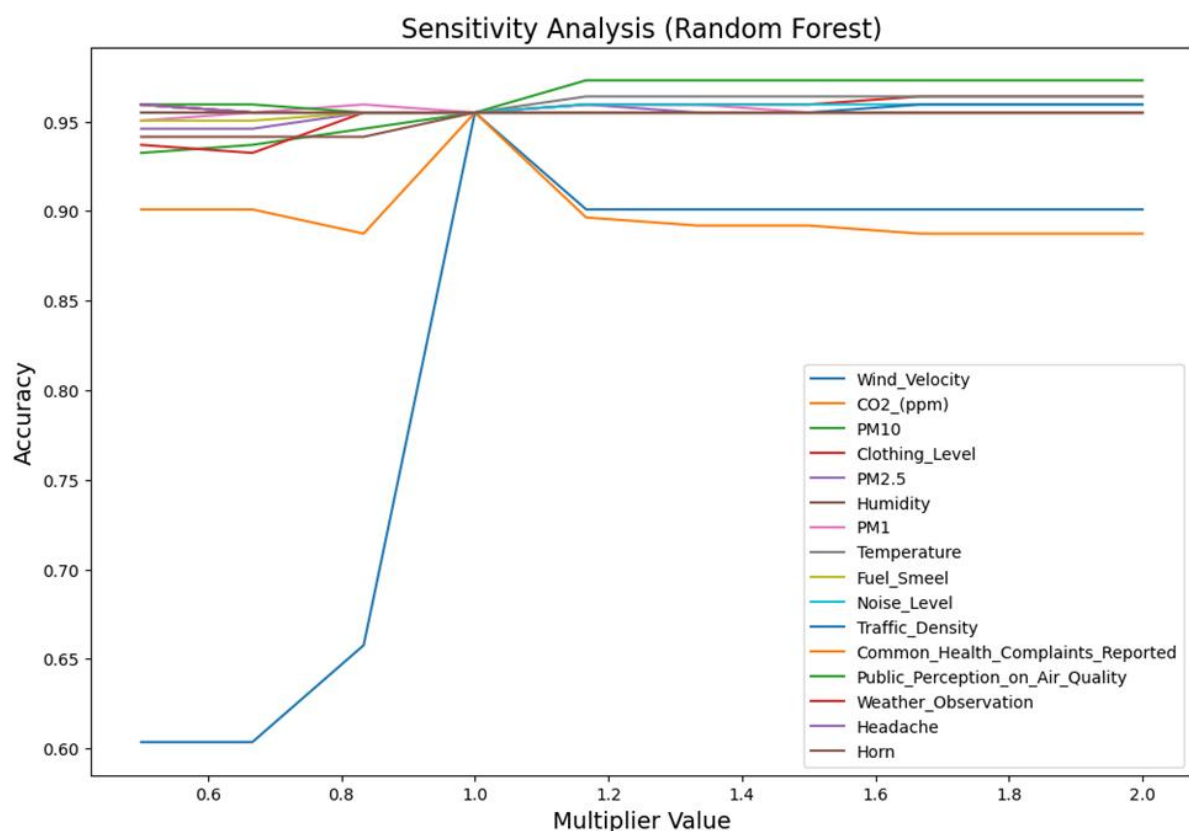
The SHAP summary plot for the best-performing model (Random Forest) is shown in **Fig. 7** to explain how each predictor contributes towards the classification of thermal discomfort. The SHAP analysis shows that the model prediction was mainly influenced by Wind Velocity and CO₂ concentration, which had the highest mean absolute SHAP values. The largest contributions were from Wind Velocity with an approximate mean SHAP value of 0.16 and CO₂ concentration with an approximate mean SHAP value of 0.12. It shows that variations in microclimatic airflow and pollution deposition of roadways were the most significant parameter to forecast thermal discomfort of road users for Dhaka city.

Moderate but meaningful contributions to model output were obtained by other variables. The contributions of Clothing Level and PM₁₀ were about 0.04, and the contributions of Humidity, PM₁, and PM_{2.5} were smaller, ranging from 0.02 to 0.03. Other variables like Weather Observation, Temperature, Traffic Density, Horn, Public Perception on Air Quality, Fuel Smell, Common Health Complaints Reported and Headache had relatively small SHAP values. Nevertheless, their addition did not detract from the general interpretability of the model but added to the environmental, traffic and perception factors affecting thermal discomfort.

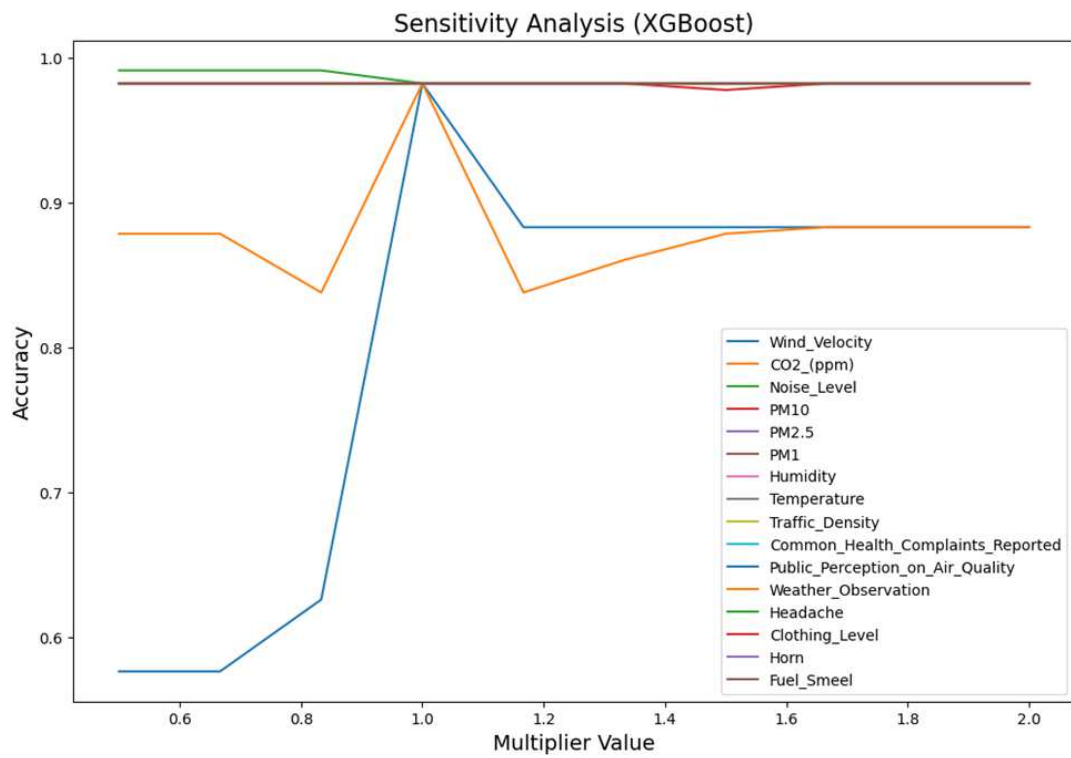
The overall results of the SHAP model showed that the RF model was not dependent on a single predictor, but rather that thermal discomfort was classified based on the interactions of the meteorological variables, the air-quality indicators, and the variables related to exposure. It is observed that Wind Velocity and CO₂ concentration has the highest importance indicating that thermal discomfort on major roadways in Dhaka is strongly associated with the microclimatic variation and pollutant exposure condition. Thus, the SHAP summary plot enhances the explainability of the best performing model and supports the robust evidence that the prediction results are consistent with the environmental exposures that occur along roadways.

3.7 Sensitivity Analysis

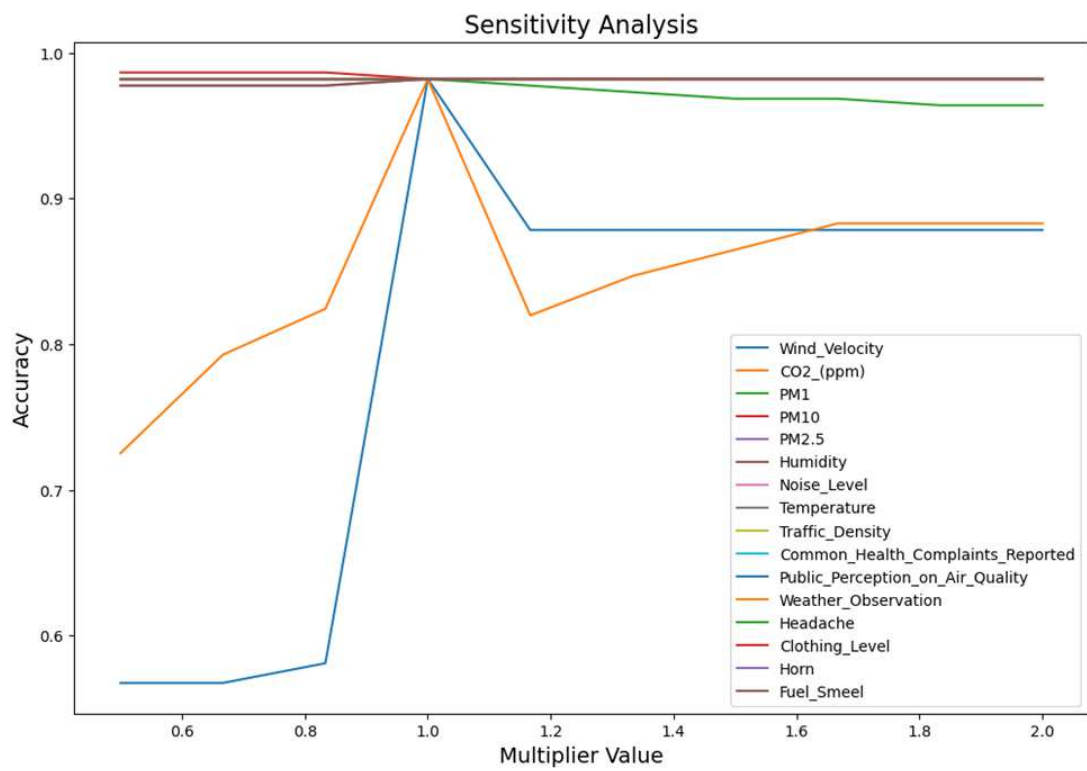
A sensitivity analysis was performed to evaluate the validity of the predictive models and the importance of the environmental variables. This analysis accounts for the influence of the changes in input features (particulate matter (PM), noise, CO₂, temperature and humidity), on the model predictions of thermal discomfort. Sensitivity analysis quantifies the impact of each variable on the model results, giving insights into the most important factors driving thermal stress for complicated multipollutant roadway conditions. The outcomes provide information for the public health interventions and model interpretability, as they provide an identification of the most important exposures that contribute to thermal discomfort responses.



(a) RF



(b) XG Boost



(C) DT

Figure 8: Sensitivity analysis for (a) RF, (b) XGBoost, (c) DT,

The sensitivity analysis of the DT, RF, and XGBoost models is shown in **Fig. 8.** for varying values of exposure-related predictors, such as PM, noise, and CO₂, with the corresponding multiplier values ranging from around 0.5 to 2.0. All three models achieved high predictive stability around the baseline value of the multiplier, with the accuracy of the models being approximately 0.98 for XGBoost, 0.95 for RF and 0.98 for DT. The XGBoost model, on the other hand, demonstrated a noticeable impact on model performance when the exposure value deviated from the baseline, with a reduction in score to around 0.84–0.88 for lower and higher values of the multiplier as compared to a score of about 0.98 at the baseline value of the exposure. The variables related to PM and noise were comparatively stable, with the majority staying around 0.97–0.99, suggesting that the XGBoost model was not as sensitive to small-to-moderate exposure to PM and noise.

The baseline accuracy for the Random Forest model was around 0.95 at the multiplier of 1.0. When the multiplier deviated from the baseline, CO₂ showed moderate decrease, as around 0.89–0.90. Noise level and predictors related to PM had a greater level of stability, typically between 0.94–0.97. The RF model also performed a little better for noise-related variation at higher level of multipliers in which the accuracy was close to 0.97, indicating stable classification ability of the RF model under higher noise exposure. The sensitivity curve gave a more pronounced CO₂ sensitivity response for the DT model. When the multiplier was increased above the baseline, the accuracy of CO₂ was somewhat 0.73 to nearly 0.98, but then dropped off to around 0.82 to 0.88. But the PM and noise related variables were more or less constant, ranging from 0.96 to 0.99.

The general trend for all three machine learning models (Fig 9.) suggests that thermal discomfort is most sensitive to CO₂ exposure with relatively consistent effect from PM and

noise variables. The stability of PM and noise curves indicates that these parameters were more stable in terms of their contribution towards the thermal discomfort classification, while the change of CO₂ caused greater variation in the model performance. For all three models, the sensitivity pattern was relatively stable, with RF having the most stable pattern, XGBoost had a similar pattern, and DT had a more variable pattern with varying levels of changes in CO₂ exposure. The results showed the robustness of the ensemble-based models and suggested that the multipollutant exposure variables used in the model can reliably explain the thermal discomfort patterns of roadway users in Dhaka.

4. Discussion

In this study, roadway users' thermal comfort has been investigated in Dhaka employing multipollutant exposure data and machine learning models. The results indicate that the thermal discomfort ratio was a very dominant variable in the data as nearly all the observations were classified as being hot, warm, or slightly warm. The descriptive data also reveals high exposure to PM, CO₂, traffic noise and warm outdoor conditions by roadway users.

Random Forest and XGBoost relatively outperformed Decision Tree in machine learning models. CO₂ and wind velocity were also identified as important predictors of thermal comfort classification from the results of the SHAP and sensitivity analysis.

4.1 Summary of Main Findings

In this study, it was observed that multipollutant exposure on the major roadways in Dhaka was significantly correlated with thermal discomfort of road users. The results indicate that

thermal discomfort in dense urban traffic conditions is not solely due to the temperature. Instead it is determined by the collective action of air pollution, traffic noise, and CO₂ concentration, emissions from traffic, traffic congestion, horn exposure and particulate pollution. It also supports the view that the comfort of roadways should be regarded as a public health problem, particularly in dense urban areas like Dhaka, following the suggestions of previous research [57-58].

The machine learning results indicated that ensemble models achieved better prediction performance than single Decision Tree model in predicting thermal discomfort. Of particular interest, XGBoost and Random Forest showed better predictive power, suggesting that they were better able to characterize the complex and non-linear relationships between environmental exposure variables and perceived discomfort. The spatial heat map also identified a number of high-risk roadway segments that experienced more combined environmental stressors. These areas could be areas of focus for targeted public health and urban transport interventions.

That too is reflected from the descriptive results on environmental condition on the main roads of Dhaka (**table: 5**). The PM_{2.5} concentration was recorded at an average of 58.35 µg/m³, PM₁₀ concentration was 81.18 µg/m³ and PM₁ concentration was 58.18 µg/m³. The average traffic noise level was also high at 82.96 dB as well. Concurrently the mean temperature and the mean relative humidity were 32.94°C and 60% respectively suggesting warm and humid outdoor conditions in the data collection period. A combination of heat and multiple environmental pollutant exposures was observed in these exposure levels.

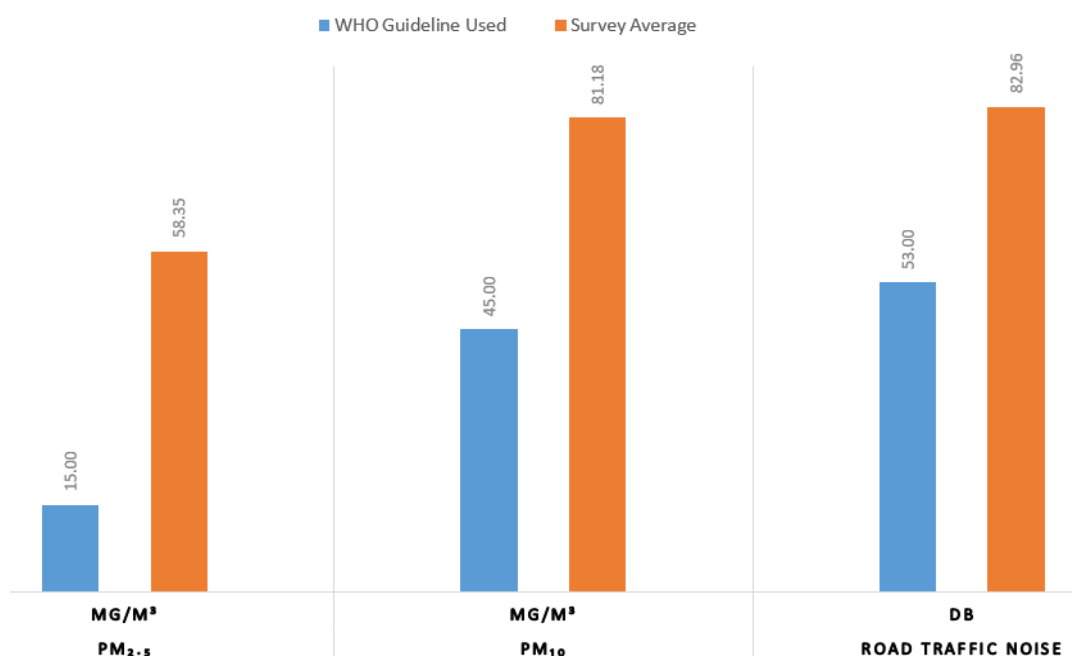


Figure 9: Comparative analysis of study area exposure levels and WHO guidelines for PM_{2.5}, PM₁₀, and road traffic noise.

Fig. 9, shows a comparative analysis of average values of the key environmental parameters fine particulate matter (PM_{2.5}), coarse particulate matter (PM₁₀) and road traffic noise, as measured through surveys conducted in the study area and as recommended by the World Health Organization (WHO). The empirical results show significant deviations from the public health standards for all the variables measured. In particular, the mean exposure to PM_{2.5} was 58.35 $\mu\text{g}/\text{m}^3$, almost four times that of the guideline set by the WHO (15.00 $\mu\text{g}/\text{m}^3$) [59]. Likewise, the ambient PM₁₀ survey average of 81.18 $\mu\text{g}/\text{m}^3$ is much higher than the recommended ambient limit for public health of 45.00 $\mu\text{g}/\text{m}^3$ [59]. From the point of view of acoustic pollution, the average of acoustic noise resulting from the road traffic noise recorded was 82.96 dB, which may also be compared with the average of 60 dB of the WHO protection guide for acoustical noise. Considering acoustic pollution, the average of the acoustical noise produced by road traffic noise recorded is 82.96 dB, which is far from the WHO protection guide for acoustical noise, which is 60 dB. All these extreme disparities highlight a significant

multipollutant burden on key traffic streets in Dhaka, with long-term implications for the health of citizens and the city's livability.

The explainable machine learning results offered additional insights into the main factors that contributed to thermal discomfort. The most important predictors of discomfort were identified using SHAP analysis, which revealed that particulate matter, traffic noise, CO₂, and temperature were among the most influential ones. This implies that air pollution and microclimatic conditions both had important impact on the level of discomfort of road users. The sensitivity analysis also showed that with increased levels of exposure, the predicted probability of thermal discomfort increased. The findings overall show that there are multiple environmental stressors that are interlinked in major roadways in Dhaka and that can significantly increase the discomfort and possible health risks to those using urban roadways.

4.2 Interpretation of Thermal Comfort Distribution

The thermal comfort distribution revealed that comfort level was very low for the majority of the road users in Dhaka. Most participants (approximately 99.4%) reported feeling hot, warm, or slightly warm on the major roadways they were asked to report on (table 4). Neutral or cool responses, on the other hand, were extremely restricted, indicating that conditions outdoors were not that comfortable during the data collection period. This is due to the interaction of high temperature, traffic emissions, lack of shade, and traffic congestion on roadways. These factors can make pedestrians, commuters, vendors, and others using the road on the street feel warmer than they really are. Hence, the finding shows that thermal discomfort is a common environmental and public health problem in the roadway environment in Dhaka [62].

But it was also a problem of class imbalance because the categories of 'hot' and 'warm' and 'slightly warm' exceeded the rest of the categories. Having few examples in neutral or cool classes meant that machine learning models that are built on these data may be biased towards the majority classes. Hence, it is important to show class-wise performance measures like precision, recall and F1-score besides the accuracy.

4.3 Random Forest and XGBoost Performed Better

The random forest and XGBoost models performed better in predicting the data than the decision tree model. The improvement can be attributed to their improved capability to represent the non-linear and interaction effects between multiple exposure variables. Roadway thermal comfort is not solely dependent upon one factor. The influence of particulate matter, CO₂, traffic noise, temperature, humidity, wind velocity, duration of exposure and individual perception [63].

The Decision Tree is easy to understand and simple, but may not reflect these complex relationships. On the other hand, the ensemble learning models Random Forest and XGBoost, which are based on several decision trees, are able to make more stable predictions and minimize model error. Random Forest works by taking average of many trees, and XGBoost works by sequentially correcting the errors. Both models are more appropriate for the multipollutant exposure analysis and thermal discomfort.

Thus, the predictions of thermal discomfort under complex urban roadway environments using ensemble models (Random Forest and XGBoost, both with F1-score of 0.96) are more accurate. This discovery paves the way for more sophisticated machine learning methods to be

applied to public health research that involves environmental exposures being affected in non-linear ways.

4.4 Interpretation of SHAP Findings

The factors derived from the SHAP analysis were found to be helpful to understand the major factors behind the predicted thermal discomfort of the road users in Dhaka [64]. For the models, the wind velocity and CO₂ concentration were consistently important predictors. It is observed that CO₂ is the most influence feature in the XGBoost model followed by wind velocity, PM_{2.5}, noise level, PM₁₀, PM₁ and humidity. The wind velocity contributed the most to the Decision Tree model, followed by CO₂, temperature, PM_{2.5}, PM₁ and other exposure variables. Likewise, in the Random Forest model, the most significant variable was wind speed followed by CO₂, clothing, temperature, PM₁₀, humidity, PM₁, PM_{2.5}, and the others.

These results show that air temperature is not the only factor that determines thermal discomfort in roadway environments. CO₂ could symbolize traffic jams, vehicle emissions and poor air circulation, wind speed could influence cooling and pollution spreading. In addition, higher concentrations of PM_{2.5} and PM₁₀ may further contribute to environmental discomfort due to the additional air pollution stress [65]. Traffic noise and horn exposure can also cause psychological and sensory stress, adding to their discomfort.

Overall, the conclusions derived from the SHAP results indicate that the thermal comfort of roadways should be considered as a result of an interaction of air pollution, air movement, heat exposure, noise, condition of clothes, and human perception. This reinforces the multipollutant approach utilized in this study and underscores the importance of explainable machine learning

for determining the critical environmental factors in dense urban traffic conditions that contribute to thermal discomfort.

4.5 Public Health Implications

The results have significant implications for public health in Dhaka, especially for users of long-term road use who are exposed to extended periods of their time spent on or near major roadways. The roads are infested with many stressors such as high level of particulate matter, CO₂, traffic noise, heat, humidity, fuel emissions, horn exposure, and congestion. Pedestrians, rickshaw pullers, traffic police, street vendors, passengers of the buses and the workers at the roadside may be exposed to such uncomfortable and polluting situations again and again in a day [66]. This can lead to higher vulnerability, headache, irritation, difficulty breathing, and physical stress, fatigue and discomfort among outdoor populations.

The high perceived level of discomfort also indicates that these environmental hazards are not just those that are monitored by instruments, but are also those that people experience. Headache and poor perception of air quality are reported, indicating the exposure to a roadway has an impact on both physical comfort and sensory well-being. The thermal discomfort issue in Dhaka's roadways should, therefore, not be taken as a micro climatic issue. It is recommended to be taken into account as a multipollutant public health issue related to air pollution, heat stress, noise exposure and human perception [66-67].

High-risk roadway segments can be identified to guide city planning decisions for interventions [68]. Actions include enhanced road-side shading and green infrastructure, optimized traffic flow, minimising idling vehicles, limiting unnecessary honking, transport modes, and safeguarding outdoor working employees [68]. Overall, the results indicate that there is a need

for the integration of urban health and transport planning to lessen multipollutant exposure and enhance the outdoor thermal comfort in Dhaka.

4.6. Comparison with Previous Studies

The existing literature on urban environmental stressors in Dhaka and other high-density cities in the South Asian region has tended to focus on stressors individually. A high level of particulate pollution is persistent and has been recorded in air-pollution studies as a result of traffic, road dust, brick kilns and seasonal stagnation [69-71]. Recent data showed the average annual PM_{2.5} concentration in the city to be 78 $\mu\text{g m}^{-3}$, which is 15.6 times higher than the WHO guideline (5 $\mu\text{g m}^{-3}$) [72]. In the present study, mean roadside PM_{2.5} was 58.35 $\mu\text{g m}^{-3}$, with corresponding PM₁₀ and PM₁ averages of 81.18 $\mu\text{g m}^{-3}$ and 58.18 $\mu\text{g m}^{-3}$. These were all above the WHO PM_{2.5} guideline, at ~ 11.7 times exposure, indicating high particulate exposure for roadway users, although lower than the citywide annual average.

The same traffic-noise studies have also reported very high acoustic burdens. Previous studies have documented average levels of about 110 dB (A) at roadside [73] and 112.9-125.6 dB(A) at traffic police, with 64 % of the participants being affected with sensorineural hearing loss [74]. The road noise level measured in the present study was 82.96 dB mean which is higher than the previously reported road noise level near a road average of 78 dB(A) [25-26] and significantly above the WHO road-traffic noise target of 53 dB Lden [60-61]. This result confirms that traffic noise is one of the most important environmental stressors that can add to the perceived discomfort.

In Dhaka, the studies of thermal comfort in outdoor environment have been conducted related to micro climate, urban form and pedestrian sensation. Sharmin et al., found impacts of deteriorating microclimatic conditions on outdoor space use and well-being [75] and other

studies related planned urban form to the intensification of the heat islands during the day [76]. Accordingly, the average road side temperature and relative humidity recorded during the study were 32.94 °C and 60 % respectively and 99.46 % of the observations were hot, warm and slightly warm.

The novelty and main contribution of this study is the integrated treatment of these stressors. The present analysis does not consist of quantification of particulate matter, noise, or thermal comfort as used in previous research, but rather multipollutant exposure, roadway microclimate, machine learning, and interpretability via SHAP values in a single predictive framework. The highest performance model obtained the AUC value of 0.96 which indicates that it is possible to systematically predict the thermal discomfort index along the main roadways of Dhaka by measuring some environmental variables. Moving beyond descriptive exposure assessment, the relative contributions of particulate matter, noise, CO₂ and heat related variables were found using SHAP [77]. When taken together, these findings fill a definite research void. The problem of air pollution, traffic noise and outdoor thermal comfort have been addressed separately in literature. This study shows evidence of a combined environmental health-risk zone by looking at pedestrians, commuters, traffic police, street vendors and transport workers all subjected to heat, particulate and noise exposure simultaneously on major roadways. SHAP supports applications in heat-health warning systems, pedestrian infrastructure planning, roadside shading, emission control and integrated urban environmental management due to its high predictive performance (AUC = 0.96) and transparency of the model.

4.7. Strengths of the Study

This study has a number of methodological and practical merits. First, it had a relatively large sample of 1109 participants, enabling the robustness of the analysis and the reliability of the model outputs. The large number of roadway users also enabled the study to be conducted in a variety of exposure and discomfort levels in a very busy, urban traffic environment.

Secondly, the study relied on exposure data from the field and not simulated or secondary environmental information. The analysis related the objective environmental conditions measured by the sensors to the subjectively reported thermal discomfort in an interview-based manner, thus linking objective and subjective data in real time. This integration enhanced the public health significance of the findings as it was based on the actual exposure conditions experienced by people living in Dhaka along the major roadways.

Third, the study took more than one pollutant into account rather than excluding one pollutant. This is a key asset since the extent of discomfort and health risk experienced by road users is typically determined by the joint exposure to air pollutants, meteorological conditions, and the road traffic situation. The multipollutant approach can thus give a closer approximation to the environmental stress imposed by roadsides.

Fourth, the study used multiple machine learning models instead of a single algorithm. This comparative modelling procedure enabled the identification of the most appropriate predictive model, and minimised the danger of being led to erroneous conclusions by the structure of one model. Furthermore, the application of SHAP-based explainability enhanced the model's transparency by revealing the impact of each variable on the thermal discomfort prediction.

Lastly, sensitivity analysis was performed, further enhancing the reliability and interpretability of results. It helped to quantify the effects of changes in major exposure variables on their predicted discomfort. In general, the study has made significant contributions to urban environmental health research in Dhaka, due to the collection of large-scale participant data,

the field-based measurements, multipollutant modelling, explainable machine learning, and public health interpretation.

5. Urban Planning and Policy Implications

The results of this study indicate that heat stress should not be ignored in urban planning and public health policies in Dhaka and it should be taken into consideration with exposure to multiple pollutants on the roadways. Heat is not the only factor to which road users are exposed; they are also exposed to particulate matter, CO₂, traffic noise, dust, vehicle emissions, lack of shade, and poor pedestrian conditions [16, 71,78] . Thus, interventions should aim to decrease the combined environmental stress instead of focusing on each environmental factor individually.

The spatial heat map may be used to identify areas on the roadway with high risk of thermal discomfort and high exposure to pollutants. Roadside tree plantation, shaded footpaths and shaded bus stops, green corridor development should be prioritized at these locations [79]. More plants along the roads can decrease direct solar radiation, enhance local cooling and help air quality [79]. Likewise, pedestrian walkways and bus parking areas that are shaded can help lower heat exposure for pedestrians, street vendors, traffic police and other individuals who walk on the street every day.

Traffic related intervention is also key. The city authorities should increase the control of traffic emissions, encourage the use of low-emission vehicles and other forms of public transport, enhance the quality of the inspection systems for vehicles, and limit the number of vehicles idling in overcrowded zones, as CO₂, particulate matter and noise were significant factors that influenced discomfort [80]. Other dust control methods, like regularly cleaning roads, dust

management during construction, and covering of loose materials while they are being transported, can help minimize the amount of particulates involved. Noise control can be addressed by better traffic controls, horn use controls, speed controls, and better road design [81].

A conceptual framework of recommended roadway thermal discomfort and multipollutant exposure mitigation planning and policy actions on major roadways in Dhaka is presented in fig 11. The framework is organized around three pillars that all focus on enhancing urban microclimates and public health. In addition, Cooling and Greening Measures are based on Nature-based Solutions such as Roadside Tree Plantation, Shaded Footpaths, Shades for Bus Stops and development of Green Corridors that all together help to mitigate the urban heat island effect by reducing ambient temperatures. Secondly, Pollution and Exposure Control strategies address the environmental stressors by implementing stringent traffic emission controls, active dust controls and noise control measures. Third, Protection, Mobility and Monitoring initiatives are systemic, with the aim of supporting vulnerable commuters with improved pedestrian infrastructure, the heat warning system and high risk road monitoring by automated surveillance.

These multi-sectoral actions combined provide an integrated approach to making Dhaka's key transport corridors safer, more climate resilient, and health protective, based on evidence (fig.10).

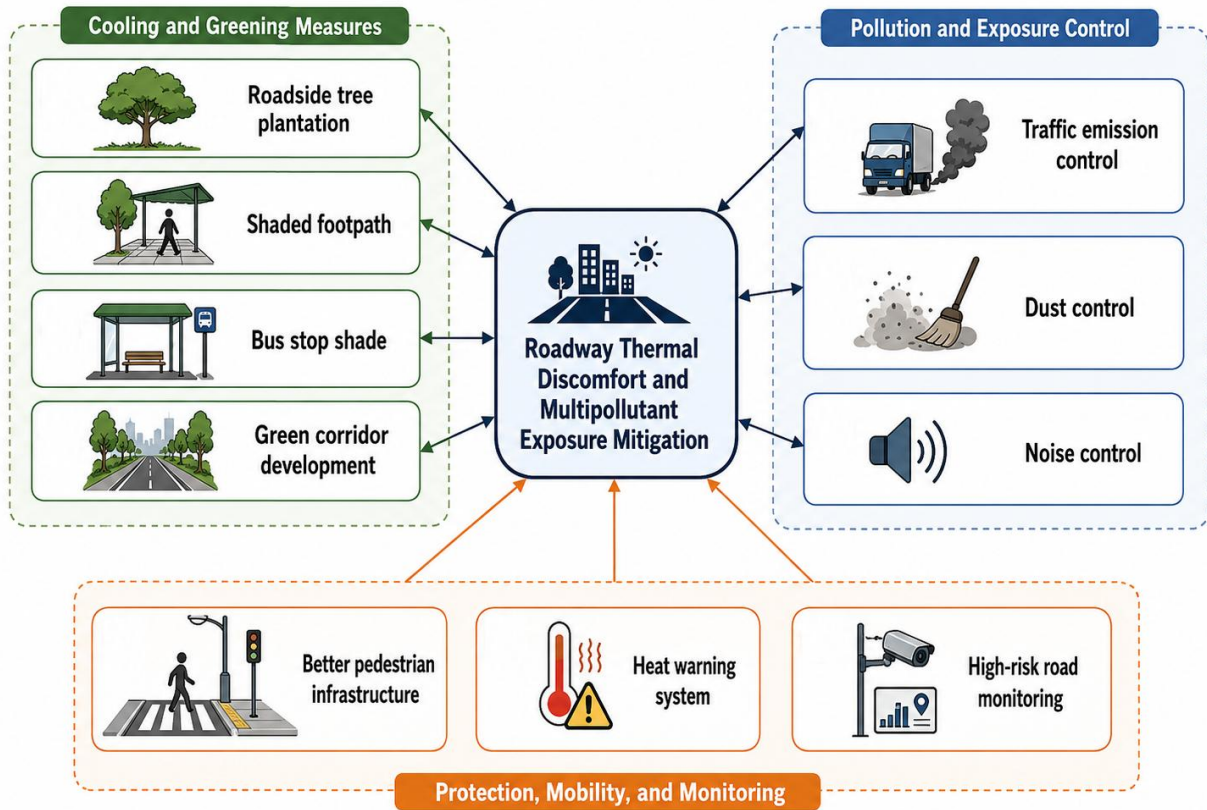


Figure 10: Recommended urban planning and policy actions for major roadways in Dhaka.

The SHAP results can be used to guide evidence-based decision making because they allow knowing which exposure variables to target first, and the sensitivity analysis can be used to understand the relative importance of each exposure variable. If, for instance, a road section has high predicted degree of discomforts related to poor ventilation, high CO₂ and high particle levels, then possible measures can be identified that can be implemented on the road to improve the traffic flow, introduce green buffers and monitor pollution. Likewise, noise and heat sensitive areas could require pedestrian infrastructure with shading and noise barriers.

Lastly, a system of monitoring high-risk roads should be created in Dhaka, which could integrate the air pollution, temperature, humidity, wind velocity and noise data [82]. During very hot days, a warning system for road users could be of assistance. Overall, the study offers a feasible combination of explainable machine learning, spatial heat map and exposure data to

help inform urban planning. These types of interventions can minimize exposure to pollutants, enhance thermal comfort outside, and safeguard the health of those who travel the major roadways frequently in Dhaka.

6. Limitations

The present study has certain limitations which need to be taken into consideration in the interpretation of the results. First, the cross-sectional design prevented causal inferences to be drawn between multipollutant exposure and thermal discomfort. Predictive associations are shown from the results, but they can't be interpreted as proof of direct causal relationships.

Second, data was collected during a limited period of time (monsoon), and may not adequately represent temperature, humidity, pollutant concentration and human thermal perception differences across seasons. The thermal discomfort that may experience in Dhaka is different during summer and winter season, future studies should consider multi-seasonal monitoring to enhance temporal representativeness.

Third, the thermal discomfort was evaluated by participants' self-responses. Self-reported perception is significant for the public health assessment but might be affected by the person's sensitivity, by the clothes she/he wears, by activity, by health state, by exposure time, by subjective perception bias. It is expected that future studies will integrate subjective responses with physiological measures to give a more holistic evaluation.

Fourth, the study was done on major roads in Dhaka, the generalizability of the findings of the study to other cities or urban context may be limited. Road geometry and traffic mix, land use,

air pollution sources and climate can vary from one location to another. Thus, the model has to be external validated in other cities before it can be applied to a wider scale.

Fifth, the machine learning models demonstrated a good predictive capacity, but they could have limited generalizability if not validated with external independent data. The models developed could be tested in other road corridors, seasons, and population groups to bolster confidence and applicability to further use.

Lastly, there can be a certain amount of measurement uncertainty in the sensor-based environmental measurements, especially if the calibration, placement, and field operating conditions change while data is being gathered. In spite of these drawbacks, the study offers good field-based evidence of the prediction of roadway thermal discomfort from multipollutant exposure and provides a solid foundation for future evolution of longitudinal, multi-seasonal, and externally validated studies.

7. Future Research

This study should be expanded in the future to include exposure variation for seasons and times. The current analysis presented useful information of thermal discomfort along the key roadways of Dhaka during the monsoon period but the risk of discomfort may differ during the summer and winter time because of the changes in temperature, humidity, precipitation, wind speed, dispersion of pollutants, and solar radiation. Further research should address repeated measurements of the different seasons and time periods to understand the dynamic nature of multipollutant exposure and thermal stress.

Other environmental, meteorological and urban form variables should also be included in future research. Pollutant concentration and perceived thermal discomfort can be affected by solar radiation, wind direction, sky view factor, road width, traffic density, building height,

vegetation coverage, pavement materials and roadside shading. Combining these parameters into one model can help increase model accuracy and give a more comprehensive picture of the built-environment factors that contribute towards discomfort in dense urban corridors.

Validation from other cities is also necessary. The proposed explainable machine learning framework should be tested in other parts of Dhaka city and other fast-growing cities in Bangladesh in the future. This would allow the generalizability of the model to be evaluated and whether the most important factors determining thermal discomfort are consistent for varying traffic, land use, and microclimates.

Another important longitudinal direction would be as well. Long-term roadside exposure in the same or similar populations may be useful to understand the consequences of chronic exposure on thermal discomfort, physiological stress, productivity, and the longer-term impacts on health. This would be beneficial for those vulnerable to road rage, like traffic police, street vendors, rickshaw pullers, pedestrians and public transport passengers who spend a long time in and around the main road.

Satellite-derived urban heat indicators, high resolution traffic data, wearable sensor measurements and real-time air quality monitoring can also be incorporated into future research. When integrated with explainable machine learning, these data sources may enhance accuracy in predictions and can be leveraged for the development of roadway-level early warning systems. Looking forward, more detailed, seasonally representative and externally validated models are needed to enhance evidence-based urban planning, climate adaptation and protection of public health in Dhaka.

8. Conclusion

In this study, an explainable machine learning model was developed to forecast a thermal discomfort for multipollutant exposure for major roadways during the monsoon season in Dhaka. The study evaluated the effects of multi-exposure to traffic-related pollutants and microclimatic conditions on perceived thermal discomfort of 1,109 roadway users in a dense urban transport environment.

The results suggest that the thermal discomfort on the major roads of Dhaka is not only a function of a single environmental exposure but rather it is a function of the interrelationships of air pollution, heat-related exposure and roadway exposure characteristics. The comparison of several machine learning models increased the predictive accuracy, and explainability using SHAP further contributed to understanding the most relevant variables for discomfort risk. The sensitivity analysis further validated the model results and facilitated the practical interpretation of the results. The results are significant since in Dhaka, users of roadways – pedestrians, traffic police, street vendors, and informal transport workers – are exposed for extended periods to polluted and thermally stressful environments. However, thermal discomfort is best addressed as a public health and urban planning problem, rather than just an environmental comfort problem.

Policy measures should focus on shaded footpaths, tree plantation along roads, bus stop shade, green corridors, control of traffic emissions, reduction of dust and noise, enhancement of pedestrian infrastructure, heat warning system, and continuous monitoring of the hot spots of the road. Overall, this research study offers an evidence-supported decision-support strategy for creating healthier, climate-smart and climate-centric road spaces in Dhaka that are more people-friendly.

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