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Indoor Air Quality and Associated Public Health Impact in AC and Non-AC Environments: A Case Study on Mymensingh, Bangladesh

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ABSTRACT

Indoo air pollution poses a critical public health risk, particularly in rapidly urbanizing regions like Bangladesh, where inadequate ventilation and climatic conditions intensify exposure risks. This study investigated seasonal and diurnal variations in indoor air quality (IAQ) across AC and Non-AC environments in Mymensingh, assessing compliance, pollutant correlations, and quantification of health risks (ELCR, HQ). Measurements of PM_1, $PM_{2.5}$, PM_{10}, TVOCs, HCHO, temperature, and humidity were taken from 56 rooms (28 AC, 28 Non-AC) during the monsoon and post-monsoon seasons using real-time monitors. During the post-monsoon season, $PM_{2.5}$ levels in Non-AC rooms reached 123.29 μg/m^3 in the afternoon, compared to 79.79 μg/m^3 in AC rooms, while PM_{10} concentrations peaked at 145.32 μg/m^3 in Non-AC environments and 89.75 μg/m^3 in AC rooms. TVOC levels were highest in AC rooms, reaching 884 μg/m^3, likely due to limited ventilation, and HCHO concentrations in AC spaces (301.14 μg/m^3) consistently exceeded WHO guidelines. Temperature and humidity influenced pollutant dynamics, with PM levels positively correlated with temperature and HCHO negatively correlated. Health risk assessments revealed significant hazards during the post-monsoon season, with children in Non-AC environments facing high estimated lifetime cancer risks (ELCR) from PM_1 (5.16E-03) and $PM_{2.5}$ (2.7E-03), while AC environments showed elevated risks from HCHO (8.75E-06). Hazard Quotients (HQ) for $PM_{2.5}$ (9.30) and PM_{10} (3.21) in Non-AC environments reached alarming levels, indicating severe non-carcinogenic risks. Source apportionment using Positive Matrix Factorization (PMF) identified distinct pollutant sources, underscoring the complex interplay of indoor and outdoor factors. Spatial analysis highlighted central urban zones as high-risk areas due to traffic emissions and commercial activities. These findings emphasize the dual burden of particulate exposure in Non-AC spaces and chemical accumulation in AC environments, influenced by seasonal shifts. Policy reforms focusing on source reduction, improved building codes, and public awareness are crucial to mitigate health disparities in tropical urban settings.

1 | Introduction

"An estimated 4.2 million premature deaths worldwide are caused by PM2.5 exposure each year."

Indoor air pollution has become a significant environmental health concern on a global scale, adversely affecting health, productivity, and quality of life (Kaushik et al. 2022; González-Martín et al. 2021). Indoor air quality (IAQ) refers to the state of air inside and around buildings, encompassing pollutant concentration, temperature, humidity, and ventilation type (Zaki and Bari 2022; D'Antonio 2021). These factors are critical for the comfort, productivity, and health of building occupants (Dimitroulopoulou et al. 2023; Tham 2016). The WHO reported that indoor air pollution caused approximately 3.8 million deaths globally in 2020, including 237,000 fatalities among children under five (WHO 2024; Tran et al., 2020). Indoor pollutant levels are often 2 to 5 times higher than outdoor levels, particularly in homes, schools, and offices (Yasmin et al. 2024; Kausar et al. 2023; USEPA 2015). This causes approximately 4.3 million deaths annually, half of which are in low and middle-income countries (WHO 2024; Nahar et al. 2016). This menace accounts for 3.6% of the total disease burden in Bangladesh (Siddique et al. 2023).

Particulate matter (PM_1, $PM_{2.5}$, PM_{10}), volatile organic compounds (VOCs), and formaldehyde (HCHO) are among the most prominent indoor pollutants (Suwanaruang, 2023) and they are impacted by meteorological variables such as temperature and humidity (Zhang et al. 2020; Mečiarová et al. 2017). These contaminants are linked to respiratory ailments, cardiovascular issues, and even cancer (Suwanaruang, 2023; Palmisani et al. 2021). PMs are classified into three groups based on the size of the particles: PM_{10} (≤ 10 µm) mostly affects the upper respiratory tract; $PM_{2.5}$ (≤ 2.5 µm) goes deep into the lungs and raises the risks of cardiovascular ailments, and PM_1 (≤ 1 µm) enters the bloodstream, causing systematic inflammation and increasing the risk of stroke and cancer. An estimated 4.2 million premature deaths worldwide are caused by $PM_{2.5}$ exposure each year, with underdeveloped and developing nations, including Bangladesh, bearing the brunt of this burden (Khan 2024; Bu et al. 2021). About 173,500 people die in Bangladesh each year as a result of air pollution, with urban $PM_{2.5}$ frequently exceeding the WHO's 5 µg/m^3 limit and PM_{10} exceeding the BNAAQS standard of 150 µg/m^3 (Islam et al. 2024; Saju et al., 2023).

TVOCs such as benzene and toluene originate from building materials, furniture, and cleaning products (Jung et al., 2024; Saeedi et al. 2024). Exposure to TVOCs can cause respiratory problems, headache, and a higher risk of cancer (Hori 2020). The World Health Organization (WHO) recommends that TVOC levels should be below 300 µg/m^3 (Tuomi and Vainiotalo 2016), but in cities, they may range anywhere from 200 to 1,000 µg/m^3 (Piasecki et al. 2018). In poorly ventilated areas, they might be over 500 µg/m^3 (Salthammer, 2022). Formaldehyde (HCHO), a known carcinogen (Group 1 classification by IARC), is widely used in the manufacture of building materials and household products, including composite wood products, glues, and various coatings (Khoshakhlagh et al. 2023). Chronic exposure to HCHO concentrations (> 0.05 mg/m^3) increases the risk of respiratory diseases and allergies (La Torre et al. 2023). The WHO recommends a 30 min exposure limit of 0.1 mg/m^3 to prevent acute effects (Wolkoff and Nielsen 2010).

Ventilation type plays a critical role in pollutant dynamics. Mechanical (AC) systems generally reduce particulate matter, but potentially accumulate CO_2 and VOCs if improperly maintained, while natural (Non-AC) ventilation often results in higher PM from outdoor infiltration (Nihar et al. 2023; Roberts et al. 2022; Nimra et al. 2021; Ji et al. 2021; Montgomery et al. 2015; Wong and Huang 2004).

Temperature and humidity significantly influence pollutant levels. A 5°C increase can raise $PM_{2.5}$ concentrations by 10%–15% and boost HCHO emissions by 20%–30%, while humidity above 70% promotes particulate resuspension, mold growth, and VOC off-gassing, sometimes raising TVOC levels to 1000–1300 µg/m^3 (Belias and Licina 2022; Cho et al. 2021; Zhou et al. 2019; Mohammed et al. 2015).

Indoor air pollution remains a critical but overlooked public health threat in South Asian urban regions (Abdul Jabbar et al. 2022). Bangladesh faces significant exposure risks due to its dense population, extreme weather events, and weak infrastructure (Hasnat et al. 2018). However, most research on indoor air pollution in Bangladesh focuses on the capital city of Dhaka, leaving other regions where a subtropical climate (34°C and high humidity), rapid urban growth, and a strained infrastructure present district IAQ challenges (Hossain et al. 2025). This research addresses the lack of localized IAQ data by studying AC and Non-AC environments, analyzing pollutants, and assessing the influence of meteorological variables. Using health risk metrics (HQ and ELCR), it benchmarks findings against the BNNAQS and WHO guidelines (Saju et al., 2023), providing actionable insights.

The primary aim of this research was to conduct a comprehensive analysis of IAQ in the context of air-conditioned (AC) and non-air-conditioned (Non-AC) environments in Mymensingh City, Bangladesh, with a focus on understanding pollutant dynamics, environmental influences, and public health risks. The specific objectives of the study were **(i)** to evaluate and compare key indoor air pollutant concentrations between AC and Non-AC environments and analyze their compliance with national (BNAAQS) and international (WHO) air quality standards, **(ii)** to analyze the influence of meteorological variables (temperature and humidity) on indoor pollutant concentrations, and **(iii)** to assess public health risks from indoor air pollution using Estimated Lifetime Cancer Risks (ELCR), and Hazard Quotient (HQ).

2 | Materials and Methods

2.1 | Study Area and Site Selection

The Mymensingh city corporation is the administrative capital of Mymensingh division and is a historic city in north-central Bangladesh (Aziz and Nilufar 2019). The city is located on the bank of the old Brahmaputra River (24°45' N latitude and

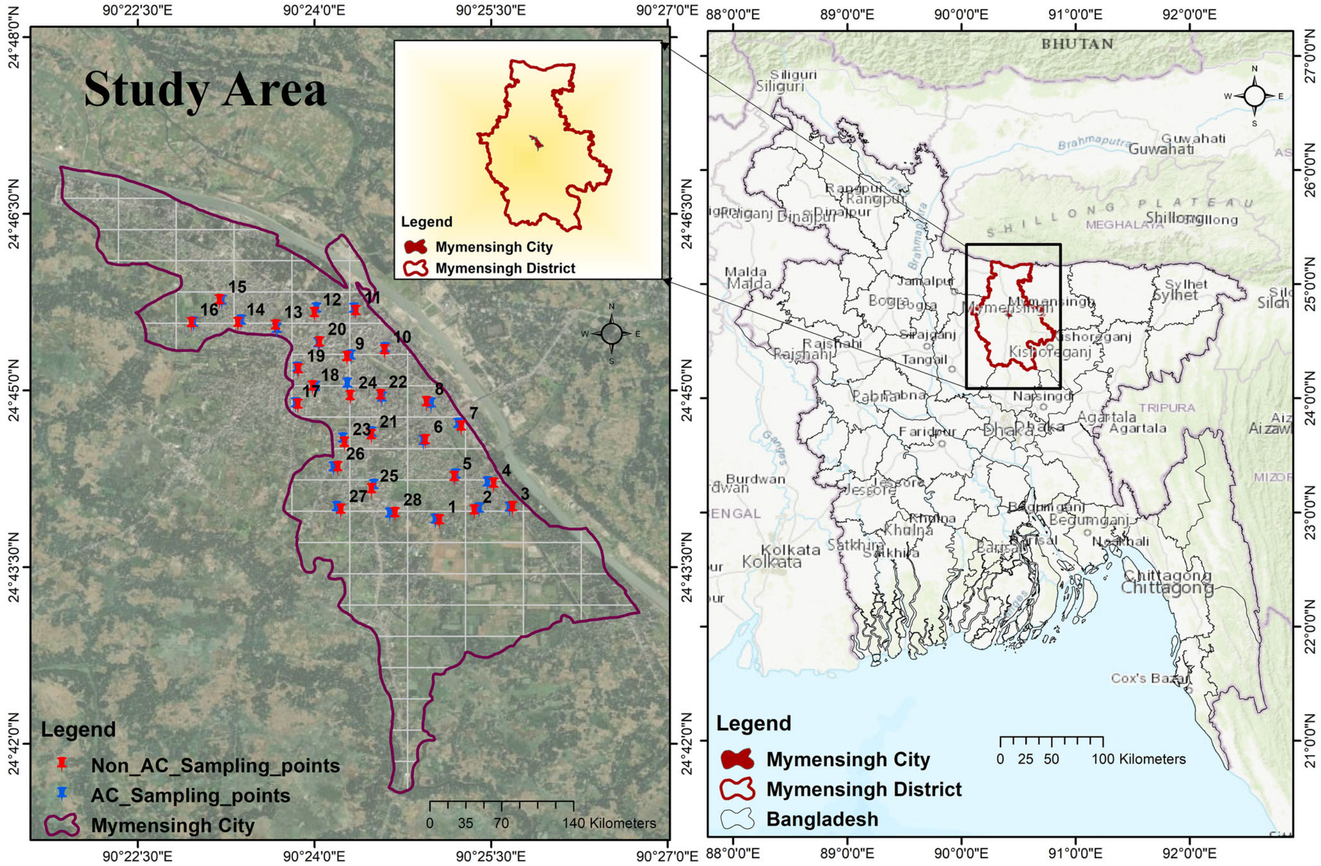

EXHIBIT 1 | Map of Mymensingh City Corporation, Bangladesh, showing the distribution of air-conditioned (AC) and non-air-conditioned (Non-AC) indoor sampling sites across seven administrative regions. Sites were selected using a systematic grid-based approach to ensure spatial coverage. [Color figures can be viewed at wileyonlinelibrary.com.]

90°23'E longitude) (Alam and Haque 2019). It covers an area of roughly 91.315 km^2 and has a population density of approximately 6500/km^2 (Begum and Ahmed 2023) (**Exhibit 1**). Mymensingh has a tropical climate with annual rainfall of ~1610 mm and a temperature ranging from 11.9–34.6°C (Kabir et al. 2022; Hossain et al. 2015). Land use is largely residential, with educational, commercial, and industrial facilities (Golap et al. 2017). Mymensingh shows extremely high ambient particulate level with mean $PM_{2.5}$ (118 ± 44 μg/m^3) (Hossain et al., 2025). People in this region is exposed to high level of air pollution primarily due to high traffic emission and dense urban development. Studies indicate that indoor pollutant levels are typically similar to outdoor levels. As a result, in densely populated region, indoor microenvironment dominates personal exposure rather than outdoor pollution. Urban housing in Bangladesh commonly relies on natural ventilation, which may be insufficient under tropical climatic conditions characterized by high humidity and seasonal temperature variation. Limited ventilation and compact indoor spaces can reduce pollutant dispersion and contribute to the accumulation of particulate matter indoors. In addition, indoor activities such as cooking have been identified as important contributors to indoor particulate concentrations, even in urban settings. Rapid urbanization, transport growth, and industrial activities together with climatic condition and household characteristics, have increased emission levels and exposure potential, making it a suitable site for IAQ and health risk assessment.

2.2 | Sampling Design

A systematic random sampling strategy was applied to ensure representative data collection across Mymensingh City Corporation. The area was first divided into equal-sized grids using a fishnet approach in ArcGIS to distribute points systematically (Rahman et al. 2022). From these, 56 rooms were purposively randomized, comprising 28 AC and 28 Non-AC rooms, covering both residential and commercial spaces. The design followed stratified random sampling, with the city divided into seven regions (Kewatkhali, Bridge, Ganginarpar, Shankipara, Noumohol, Chorpara, and Mashkanda), and AC and Non-AC rooms paired within the same region but in different buildings to control spatial variability. To capture temporal variation, measurements were obtained in two seasons, monsoon (June 2024) and post-monsoon (October 2024), and at two times of day, morning (8–11 AM) and afternoon (2–5 PM). In each season, data were collected for 25 days. This results in a total of 2800 measurements, evenly distributed across room types, seasons, and time of the day, ensuring a representative dataset for IAQ assessment.

2.3 | Measured Parameters and Monitoring Equipment

This study monitored IAQ by measuring formaldehyde (HCHO), total volatile organic compounds (TVOCs), particulate matter

EXHIBIT 2 | Specification of the IGERESS indoor air quality monitor.

Parameter	Sensor	Detection Range	Error
Particulate Matter (PM_1, $PM_{2.5}$, PM_{10})	Micro dust sensor (IR)	0-999 μg/m^3	< 5%
Formaldehyde (HCHO)	Electrochemical	0-1999 μg/m^3	< 5%
Total Volatile Organic Compound (TVOC)	Electrochemical	0-1999 μg/m^3	< 5%
Temperature (°C)		0-50°C	< 5%
Humidity (RH)		20%–99%	< 5%

(PM_1, $PM_{2.5}$, PM_{10}), temperature, and humidity, key indicators of health risks. Data were collected using the IGERESS IAQ Monitor, a portable device providing real-time, high-precision measurements. A key methodological detail should be noted here. The monitor utilized separate sensors for collecting pollutant data. As per the manufacturer's specification, particulate matter data is collected using infrared (IR) sensor. The TVOCs and HCHO is collected separate electrochemical sensor. Hence, the reported HCHO concentration is exclusive and is not a subset of TVOCs concentration. The TVOC sensor provides a composite concentration (isopropanol) equivalent for a wide range of VOC. The monitor was calibrated (for 5 min) each time before data collection and positioned at breathing height (1–1.5 m). Measurements were carried out for a total of 20 min in each room including a 5 min calibration phase. Following the calibration, 5 separate measurements were recorded after every 3 min. Data were logged on structured sheets and later organized in Microsoft Excel for further analysis. The detailed specification of the measurement instrument is presented in **Exhibit 2**.

2.4 | Statistical Analysis

The statistical analysis evaluated IAQ parameters, compared AC and Non-AC environments, assessed correlations with environmental factors, and determined associated health risks. Microsoft Excel, Python (version 3.x), and Google Collaboratory were employed for data organization, statistical testing, and visualization (Zulkipli et al. 2020; Sahoo* et al. 2019).

2.4.1 | Data Preparation

Collected data were organized and cleaned in Microsoft Excel to ensure accuracy. During the cleaning process data from 2 days in the monsoon and post-monsoon seasons were excluded due to inappropriate measurement, as these readings were taken for longer than the designated sampling period. The cleaned dataset was imported into Google Collaboratory for analysis using Python. Column names were standardized using the str.strip() function to remove extra spaces. Data for both monsoon and post-monsoon seasons, alongside WHO and BNAAQS standards, were loaded using the pandas library (Sahoo* et al. 2019).

2.4.2 | Descriptive Statistics

Descriptive statistics, including mean, standard deviation, minimum, and maximum values, were calculated for each parameter using Python's pandas and numpy libraries (Zulkipli et al. 2020). These summarized the distribution of parameters across room types, seasons, and times of day.

2.4.3 | Comparative Analysis

Data were filtered by season and room type. Missing values for target parameters (PM_1, $PM_{2.5}$, PM_{10}, TVOC, HCHO) were dropped using dropna() to ensure integrity (Nagpal and Gabrani 2019). Box plots visualized distributions, with horizontal lines denoting WHO and BNAAQS standards (Danek et al. 2022; Yudin 2021). The Shapiro–Wilk test assessed normality, guiding the selection of independent *t*-tests (normal data) or Mann–Whitney *U* tests (non-normal data) to compare room types and seasons. One-sample *t*-tests benchmarked pollutant levels against WHO and BNAAQS guidelines (Ostrowski and Menyhárt 2020).

2.4.4 | Correlation Analysis

Seasonal data were combined into a single Data Frame using concat() (Sahoo* et al. 2019). A correlation matrix for pollutants, temperature, and humidity was calculated with corr() and visualized as an annotated heatmap using a colour gradient (Danek et al. 2022; Yudin 2021).

2.5 | Source Apportionment Analysis

Source apportionment was conducted using Non-negative Matrix Factorization (NMF), a receptor-modeling technique conceptually analogues to Positive Matrix Factorization (PMF) (Lekinwala and Bhushan 2022; Brown et al. 2015). The analysis utilized five pollutant species (PM_1, $PM_{2.5}$, PM_{10}, TVOC, and HCHO) measured in indoor environments. NMF decomposes the concentration matrix (X) into a source contribution matrix (W) and a source profile matrix (H) under non-negativity constraints:

$$X = W \times H$$

where W represents source contributions and H represents source profiles.

Prior to analysis, pollutant concentrations were standardized using *z*-score normalization. Because NMF requires non-negative input data, the standardized dataset was shifted by subtracting the minimum value and adding a small constant (10^{-6}) to ensure non-negativity (Lekinwala and Bhushan 2022). The NMF model was implemented in Python using the scikit-learn library. Source apportionment was performed separately for each season and room category (Monsoon AC, Monsoon Non-AC, Post-monsoon AC, and Post-monsoon Non-AC). Solutions with two to five factors were evaluated and compared based on reconstruction error, stability of the factor profiles, and interpretability of the resulting source structure. The two-factor solution combined pollutants with distinct characteristics into broad categories. Given the limited number of pollutant species ($n = 5$), solutions containing four or five factors tended to subdivide chemically related sources and generated less meaningful source profiles (Scerri et al. 2019).

Considering the limited number of pollutant species included in the analysis, the three-factor model showed stable and well-separated source profile. Therefore, a three-factor model was selected for final source apportionment. The selected three-factor model consistently resolved: (i) particulate matter-dominated sources, (ii) HCHO-dominated sources, and (iii) TVOC-dominated sources across different seasons and ventilation conditions. The identified factors were interpreted according to their dominant pollutant loadings and their consistency across seasons and room types (Maung et al. 2022). This approach enabled the characterization of major indoor pollution sources and their relative contributions under different ventilation conditions (Rathbone et al. 2025).

Since a Python-based NMF framework was employed rather than EPA PMF software, uncertainty matrices, bootstrap analysis, displacement (DISP) diagnostics, robust mode, and BDL-specific treatments were not incorporated in the present analysis.

2.6 | Public Health Risk Assessment

> *"The assessment focused on inhalation exposure to particulate matter (PM1, PM2.5, and PM10) and gaseous pollutants (HCHO)."*

To evaluate the potential health risks associated with exposure to indoor air pollutants in AC and Non-AC rooms, a quantitative health risk assessment approach was employed (Saju et al., 2023). The assessment focused on inhalation exposure to particulate matter (PM_1, $PM_{2.5}$, and PM_{10}) and gaseous pollutants (HCHO) (Saju et al., 2023; Chen et al. 2017). The health risk assessment followed the United States Environmental Protection Agency (USEPA) Risk Assessment Guidelines (USEPA 2015) and included the estimation of both carcinogenic and Non-carcinogenic risks. The risk assessment was carried out through the estimation of Excess/Estimated Lifetime Cancer Risk (ELCR) and Hazard Quotient (HQ) for different exposure scenarios (Sidibe et al. 2022; Chen et al. 2017).

2.6.1 | Exposure Assessment

The collected data were used to estimate the exposure concentration (EC) for each pollutant, which served as an input for health risk calculations.

The Lifetime Average Daily Dose (LADD), a key parameter in risk estimation, was calculated using Equation (1) (Sakunkoo et al. 2022; Yunesian et al. 2019).

$$LADD = \frac{CxIRxEDxEF}{BWxAT} \quad (1)$$

where:

C = Measured concentration of the pollutant (μg/m^3)

IR = Inhalation rate (m^3/day)

ED = Exposure duration (years)

EF = Exposure frequency (days/year)

BW = Body weight (kg)

AT = Averaging time (lifetime exposure duration in hours, that is, 70 years x 365 days x 24 h for carcinogenic risk or total exposure duration for non-carcinogenic risk)

The LADD was calculated for different indoor environments (AC vs. Non-AC) across monsoon and post-monsoon seasons to understand seasonal variations in health risks. The risk estimates were compared with international safety standards to determine the potential impact on human health.

2.6.2 | Non-Carcinogenic Risk Assessment

The non-carcinogenic health risks of air pollutants were assessed using the Hazard Quotient (HQ) and Hazard Index (HI). The HQ was calculated using Equation (2) (Saju et al., 2023; Yunesian et al. 2019).

$$HQ = \frac{LADD}{RfD} \quad (2)$$

Where:

HQ = Hazard Quotient

LADD = Lifetime Average Daily Dose (μg/kg/day)

RfD = Reference Dose (μg/kg/day)

The Reference Dose (RfD) was estimated using the following Equation (3) (Rostami et al. 2019).

$$RfD = \frac{RfCxIR}{BW} \quad (3)$$

Where:

RfC = Reference Concentration of pollutants (μg/m^3)

IR = Inhalation Rate (m^3/day)

BW = Body Weight (kg)

2.6.3 | Carcinogenic Risk Assessment

The Excess Lifetime Cancer Risk (ELCR) was calculated for PM_1, $PM_{2.5,}$ and formaldehyde (HCHO) as they are classified as probable human carcinogens. The ELCR was estimated using Equations (4), (5), and (6) (Saju et al., 2023; Yunesian et al. 2019).

$$ELCR\ (PM_1) = LADD\,(PM_1)\,xSF\,(PM_1) \tag{4}$$

$$ELCR\,(PM_{2.5}) = LADD\,(PM_{2.5})\,xSF\,(PM_{2.5}) \tag{5}$$

$$ELCR\ (HCHO) = LADD\,(HCHO)\,xSF\,(HCHO) \tag{6}$$

Where:

SF = Slope factor (kg day/μg), derived from the inhalation unit risk (IUR).

LADD = Lifetime Average Daily Dose (μg/kg/day).

The Slope Factor (SF) was calculated using Equation (7) (Saju et al., 2023).

$$SF = \frac{IUR}{BW\,xIR} \tag{7}$$

Where:

IUR = Inhalation unit risk ($\mu g/m^3$) $^{-1}$

BW = Body weight (kg)

IR = Inhalation rate (m^3/day)

Exhibit 3 presents the key parameters and reference values for assessing the non-carcinogenic and carcinogenic health risks from exposure to particulate matter (PM_1, $PM_{2.5}$, PM_{10}) and formaldehyde (HCHO).

Critical age-dependent variables include inhalation rate (IR) and body weight (BW), which are essential for calculating the lifetime average daily dose (LADD) (Saju et al., 2023; Yunesian et al. 2019). The assessment also incorporates exposure frequency (EF) and exposure duration (ED). Reference concentrations (RfC), and inhalation unit risk (IUR) values for the selected parameters are presented in Exhibit 3.

3 | Results

This study characterized IAQ in Mymensingh City by analyzing particulate matter (PM_1, $PM_{2.5}$, PM_{10}), TVOCs, formaldehyde (HCHO), temperature, and relative humidity. Results are presented for AC and Non-AC environments across monsoon and post-monsoon seasons, benchmarked against WHO and BNAAQS guidelines. Indoor concentrations are discussed in the context of WHO guidelines and Bangladesh National Ambient Air Quality Standards (BNAAQS), which serve as reference points for potential health risks, even though they are primarily set for outdoor air. This comparison is justified because indoor particulate matter is often influenced by outdoor infiltration, and using these standards allows for a benchmark to evaluate potential exposure and associated health risks in indoor environments, consistent with previous IAQ studies.

3.1 | Pollutant Concentration in AC and Non-AC Environments

3.1.1 | Particulate Matter (PM_1, $PM_{2.5}$, PM_{10})

PM concentrations were consistently higher in Non-AC rooms. PM_1 levels surged post-monsoon, with afternoon levels ranging 67–105 $\mu g/m^3$ (Non-AC) versus 18–83 $\mu g/m^3$ (AC). $PM_{2.5}$ concentrations in Non-AC rooms during the post-monsoon season (110.29–123.29 $\mu g/m^3$) exceeded the WHO guideline (15 $\mu g/m^3$) and neared the BNAAQS standard (65 $\mu g/m^3$). AC rooms showed lower, yet significant, levels (67.46–79.79 $\mu g/m^3$). A similar trend was observed for PM_{10}, with post-monsoon afternoon averages in Non-AC rooms reaching 145.32 $\mu g/m^3$, exceeding the WHO standard (45 $\mu g/m^3$) but remaining below the BNAAQS threshold (150 $\mu g/m^3$) (**Exhibit 4**).

3.1.2 | Gaseous Pollutants (TVOCs and HCHO)

An inverse pattern was observed for gaseous pollutants. In contrast to particulate matter, TVOC levels were notably higher in AC environments. During the monsoon, AC rooms averaged 470.43 $\mu g/m^3$ (morning) and 641.32 $\mu g/m^3$ (afternoon), compared to 385.89 $\mu g/m^3$ and 527 $\mu g/m^3$ in Non-AC rooms. Post-monsoon levels increased significantly, with AC rooms peaking at 884 $\mu g/m^3$ in the afternoon. Formaldehyde (HCHO) concentrations also prevailed in AC rooms, consistently exceeding the WHO guideline (100 $\mu g/m^3$) with monsoon afternoon averages of 313.46 $\mu g/m^3$. Although Non-AC rooms showed lower levels (145.71 $\mu g/m^3$), post-monsoon averages still increased to 166.46 $\mu g/m^3$ in the afternoon (**Exhibit 5**).

3.1.3 | Meteorological Variables (Temperature and Humidity)

Temperature and humidity play a crucial role in IAQ, influencing the concentration and behavior of various airborne pollutants.

Temperatures in AC rooms remained consistently lower and more stable across both seasons. For instance, during the monsoon season average temperature in AC environments was 26°C (morning) and 27°C (afternoon), while in Non-AC environments it reached 28°C and 30°C, respectively. The post-monsoon period showed even greater divergence, with Non-AC environments frequently peaking at 32°C during the afternoon (**Exhibit 6a**).

Humidity patterns showed clear differences between the two environments. Non-AC spaces consistently had higher humidity levels. This was especially noticeable during monsoon mornings. Readings in Non-AC rooms averaged 96%, while AC rooms stayed around 75%. The air conditioning systems successfully kept humidity within a moderate 45%–95% range. In con-

EXHIBIT 3 | Parameters and reference values for health risk assessment of PM_1, $PM_{2.5}$, PM_{10}, and formaldehyde (HCHO) in Mymensingh City.

Parameters	Symbol	Unit	Age Group/ Year Range: Children 3 to < 6	Teenage 11 to < 16	Adult 21 to < 61		Sources
Inhalation Rate	IR	mg/Day	12	16.3	16		(Saju et al., 2023; Yunesian et al. 2019)
Body Weight	BW	Kg	18.6	56.8	80		(Saju et al., 2023; Yarmohammadi et al. 2016)
Exposure Frequency	EF	Day/Year	365	365	365		(Saju et al., 2023)
Exposure Duration	ED	Year	3	5	49		(Saju et al., 2023; Mehrizi et al. 2017)
			PM_1	**$PM_{2.5}$**	**PM_{10}**	**HCHO**	
Reference Concentration	RfC	μg/m³		15	50	0.007	(Saju et al., 2023; Mehrizi et al. 2017)
Inhalation Unit Risk	IUR	μg/m³	0.0215	0.008		1.1E-05	(Saju et al., 2023; Chen et al. 2017)

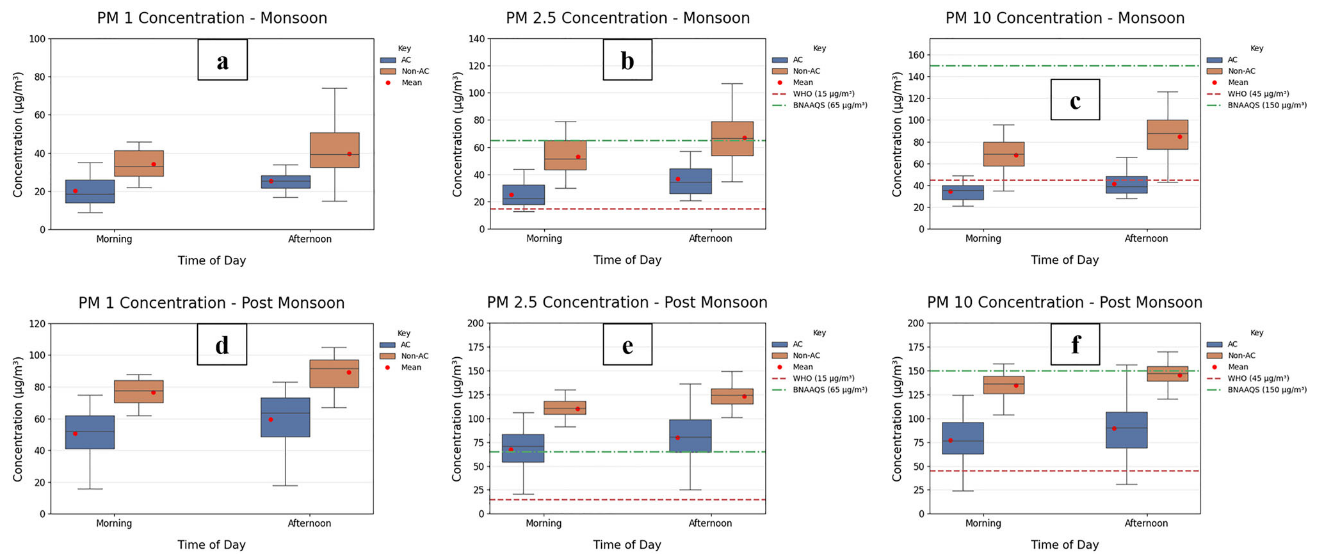

EXHIBIT 4 | Indoor concentrations of PM_1, $PM_{2.5}$, and PM_{10} (μg/m³) in AC and Non-AC environments during monsoon (a-c) and post-monsoon (d-f) seasons. Data are shown for morning and afternoon periods. Dashed lines indicate WHO and BNAAQS guideline values. [Color figures can be viewed at wileyonlinelibrary.com.]

trast, Non-AC environments recorded levels from 63% to 98%. High readings above 90% were common there in both seasons (Exhibit 6b). This notable difference in moisture levels between room types likely influences how pollutants build up and behave indoors.

3.2 | Correlation Analysis of IAQ Parameters and Meteorological Variables

The correlation heatmap of IAQ parameters provides critical insights into the interrelationships among particulate matter (PM_1, $PM_{2.5}$, PM_{10}), TVOCs, formaldehyde (HCHO), temperature, and humidity in both AC and Non-AC environments across monsoon and post-monsoon seasons.

The correlation heatmap reveals significant relationships among indoor air pollutants and meteorological variables (**Exhibit 7**). PM_1, $PM_{2.5}$, and PM_{10} are highly correlated with each other (r = 0.96, 0.98, and 0.95, $p \leq 0.001$), suggesting they come from similar sources, such as outdoor air infiltration, indoor activities, or combustion processes. TVOC shows moderate to weak correlations with PM_1 ($r = 0.33$, $p < 0.001$), $PM_{2.5}$ (r =

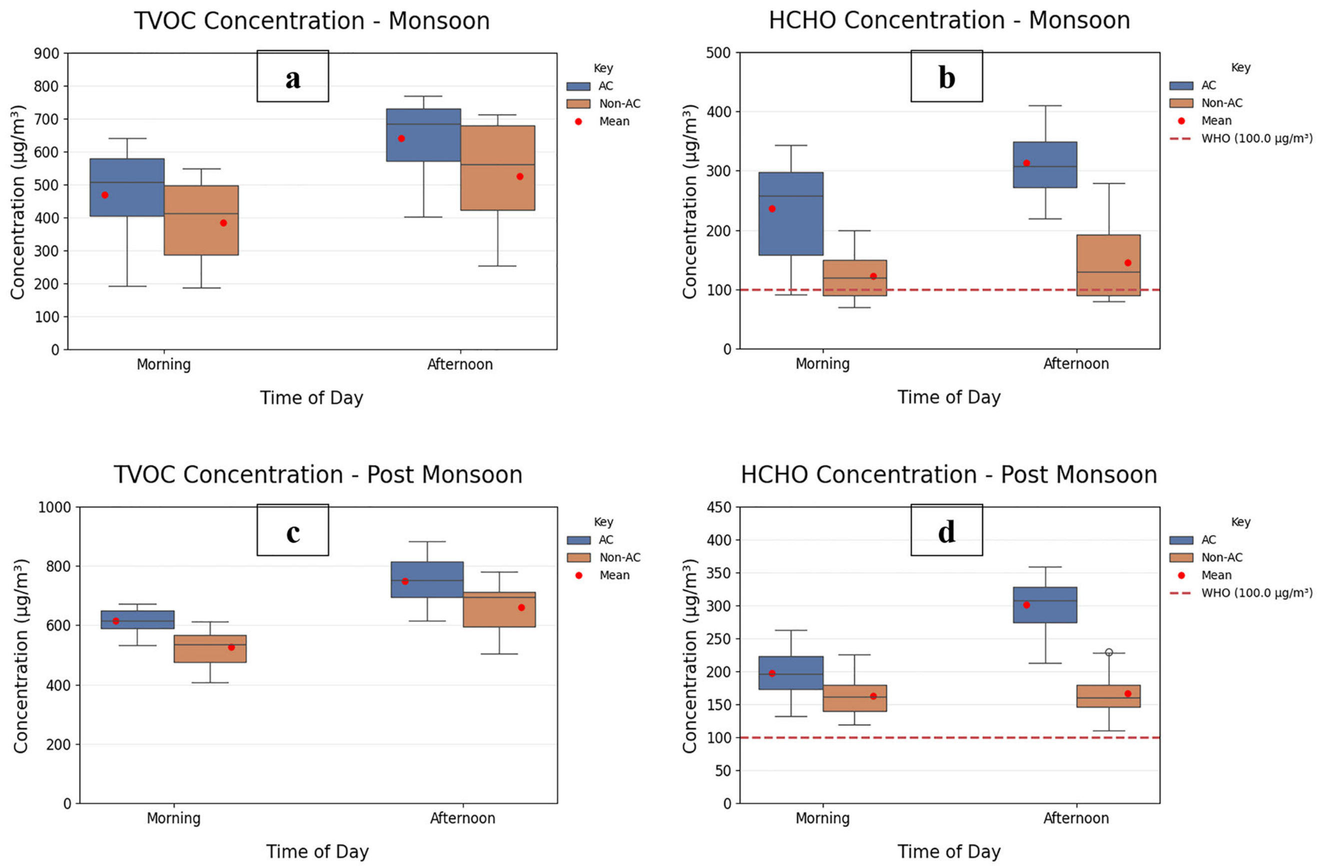

EXHIBIT 5 | Concentrations of total volatile organic compounds (TVOCs) and formaldehyde (HCHO) in AC and Non-AC environments during monsoon (a-b) and post-monsoon (c-d) seasons. Values are expressed in µg/m^3 for morning and afternoon periods. The dashed line in HCHO panels represents the WHO exposure guideline (100 µg/m^3). [Color figures can be viewed at wileyonlinelibrary.com.]

0.29, $p < 0.001$), and PM_{10} ($r = 0.23$, $p < 0.001$), indicating that particulate matter and gaseous pollutants often appear together, possibly due to emissions from household products, cooking, or human activities. A moderate positive correlation was also observed between TVOC and HCHO ($r = 0.46$, $p < 0.001$), indicating potential contributions from common indoor emission sources. Temperature is positively correlated with PM_1 ($r = 0.48$, $p < 0.001$), $PM_{2.5}$ ($r = 0.55$, $p < 0.001$), and PM_{10} ($r = 0.57$, $p < 0.001$), meaning warmer conditions may lead to higher particle concentrations, possibly due to resuspension or secondary particle formation. The correlation heatmap further reveals that temperature has a negative correlation with HCHO ($r = -0.39$, $p < 0.001$), indicating that lower temperatures tend to result in higher HCHO levels. This finding aligns with the observed trend in cooler AC environments, where temperatures are lower, yet HCHO concentrations are higher than in Non-AC rooms. Relative humidity showed significant negative correlations with TVOC ($r = -0.32$, $p < 0.001$) and HCHO ($r = -0.46$, $p < 0.001$), suggesting that lower humidity conditions may favor the accumulation of these pollutants. In contrast, correlations between humidity and particulate matter were weak and statistically non-significant with PM_1 ($r = -0.09$, $p > 0.05$), $PM_{2.5}$ ($r = -0.01$, $p > 0.05$), and PM_{10} ($r = 0.04$, $p > 0.05$), indicating a limited influence of humidity on indoor particle concentrations within the study environments.

3.3 | Source Apportionment Analysis Using PMF (Positive Matrix Factorization) Model

A three-factor positive matrix factorization (PMF) model was implemented using non-negative matrix factorization (NMF) to statistically describe the source profile of indoor air pollutants (**Exhibit 8**). The analysis was conducted separately to identify sources as per seasonal and microclimatic conditions. The model successfully resolved distinct particulate dominated and chemically dominated sources demonstrating physical interpretability and robust source apportionment.

PMF model, during the monsoon season found clearer source separation in AC and Non-AC environments. In AC environment one factor was primarily influenced by particulate matter (PM_1, $PM_{2.5}$ and PM_{10}) with negligible TVOC and HCHO. It indicates a general particulate dominated source affected by outdoor infiltration and indoor resuspension. A second factor shows high loadings of TVOC (1.42) with moderate $PM_{2.5}$ an PM_{10} levels. It suggests pollutants come from indoor activities like cooking and consumer product usage. The third factor was mostly dominated by HCHO (4.02) and PM_1 (1.23), indicating emission from building materials and furniture (**Exhibit 8a**). In non-AC environments, a factor was dominated by particulate matter suggesting outdoor infiltration. A second factor had a lot

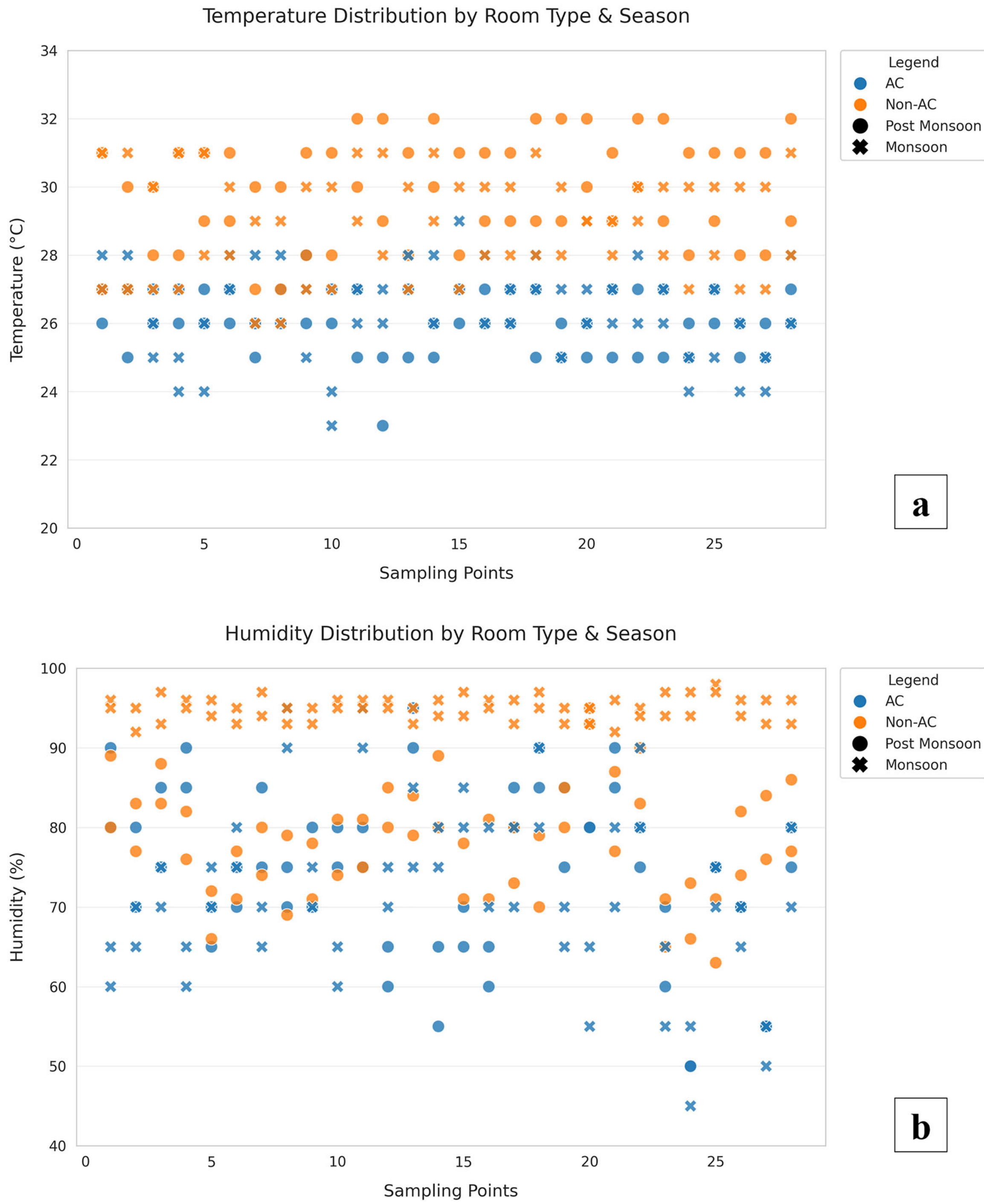

EXHIBIT 6 | Distribution of meteorological variables in AC and Non-AC environments during the monsoon and post-monsoon season: (a) Temperature, (b) Humidity. [Color figures can be viewed at wileyonlinelibrary.com.]

of HCHO (1.29) and a little bit of PM, while a third factor had a lot of TVOC (3.24) and a little bit of HCHO and PM. This means that there was a separate source of volatile chemicals. Non-AC circumstances had greater chemical signals and less source separation than AC settings (Exhibit 8b). During the post-monsoon season, AC environment has a particulate dominated source factor with moderate TVOC loading (0.52). It indicates an association between particulate and chemical emission during drier condition. An HCHO-dominated factor (1.20) suggests that indoor materials may emit formaldehyde constantly. A third source factor shows high loading of TVOC (2.54) and HCHO (1.57), suggests that there might be a strong source of chemical (Exhibit 8c). Non-AC environment showed greater source complexity. Particulate matter and TVOC domination were seen in a source factor that suggest there might be emission form cooking and indoor-outdoor infiltration. One factor stood out

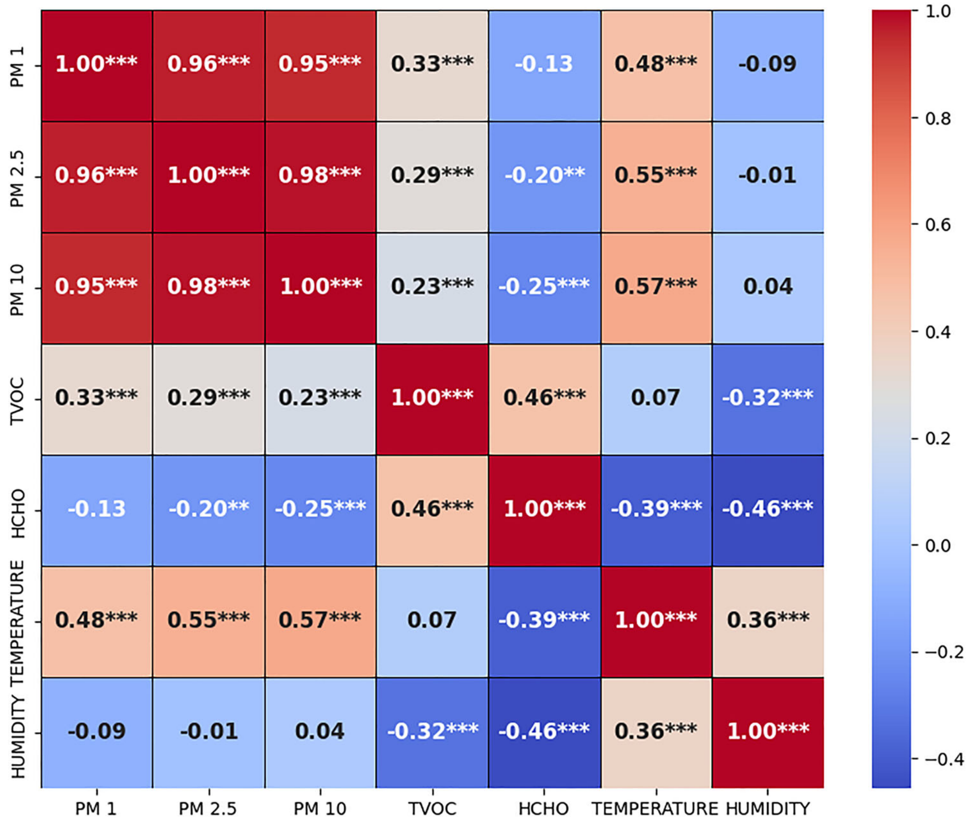

EXHIBIT 7 | Pearson correlation coefficients among PM_1, $PM_{2.5}$, PM_{10}, TVOCs, HCHO, temperature, and relative humidity across all seasons and environments. Values represent Pearson's correlation coefficients (r). Asterisks denote statistical significance levels (* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$). [Color figures can be viewed at wileyonlinelibrary.com.]

with very high PM_1 (2.20) and HCHO (2.36), which means that it was a strong source of ultrafine particles and formaldehyde (Exhibit 8d).

3.4 | Public Health Risk Assessment

This section presents the results of the health risk assessment for IAQ in Mymensingh City Corporation, focusing on both carcinogenic and non-carcinogenic risks. The Estimated Lifetime Cancer Risk (ELCR) was assessed for three age groups, children (3 to < 6 years), teenagers (11 to < 16 years), and adults (21 to < 61 years), across AC and non-AC environments. The analysis considered key pollutants (PM_1, $PM_{2.5}$, and HCHO) and seasonal variations between monsoon and post-monsoon periods. Non-carcinogenic risks were evaluated using the Hazard Quotient (HQ) for $PM_{2.5}$ and PM_{10}. The inhalation risk models and age-specific exposure parameters of USEPA were used, and spatial maps were produced via GIS interpolation to identify high-risk hotspots. To ensure clarity and comparability, the results are summarized in descriptive statistics (mean, standard deviation, minimum, maximum, and median) across pollutants, age groups, environments, and seasons. Spatial distribution patterns, generated through GIS-based interpolation, are provided separately in the supplementary materials to illustrate high-risk hotspots and localized variations. This dual presentation highlights both the statistical magnitude and spatial dynamics of public health risks.

3.4.1 | Estimated Lifetime Cancer Risk (ELCR) Analysis

This section presents the analysis of lifetime cancer risk associated with exposure to selected indoor air pollutants (PM_1, $PM_{2.5}$, and formaldehyde).

3.4.1.1 | ELCR (PM_1: Monsoon and Post-Monsoon). Exhibit 9 illustrates the descriptive statistics of ELCR values for PM_1 during the monsoon and post-monsoon seasons in both AC and Non-AC environments across three age groups.

The Estimated Lifetime Cancer Risk (ELCR) associated with PM_1 exposure showed clear variations across age groups, environments, and seasons (Exhibit 9). During the monsoon, ELCR values in AC environments were comparatively lower, with mean risks of 1.42E-03 for children, 1.53E-04 for teenagers, and 7.69E-05 for adults. In contrast, non-AC environments presented higher risks, particularly for children, who recorded a mean ELCR of 2.30E-03, almost 1.6 times greater than their AC counterparts.

In the post-monsoon season, ELCR values rose substantially across all groups. Children in non-AC environments exhibited the highest risk, with a mean ELCR of 5.16E-03, compared to 3.42E-03 in AC settings. Teenagers and adults followed a similar pattern, with risks in non-AC environments (5.53E-04 and 2.79E-04, respectively) exceeding those in AC environments (3.67E-04 and 1.85E-04, respectively).

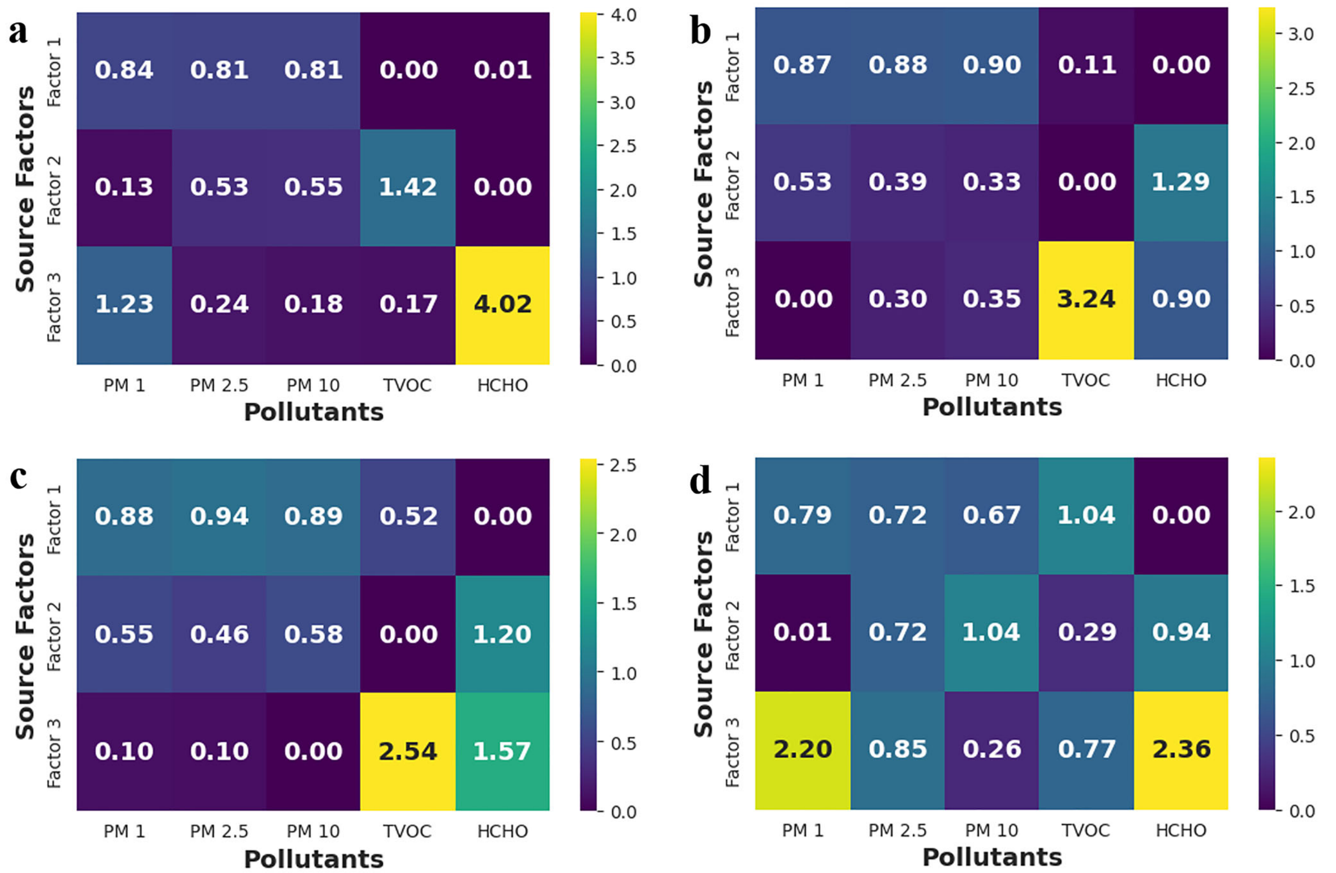

EXHIBIT 8 | PMF derived source profile of indoor air pollutants across different seasons and microclimatic condition (a) Monsoon AC (b) Monsoon Non-AC (c) Post Monsoon AC (d) Post Monsoon Non-AC. Bars represent normalized factor loadings of particulate and gaseous pollutants. [Color figures can be viewed at wileyonlinelibrary.com.]

EXHIBIT 9 | Descriptive statistics of Excess Lifetime Cancer Risk (ELCR) for PM_1 exposure by age group and indoor environment.

Seasons	Environment	Age Group	Mean ELCR	SD
Monsoon	**AC**	Children	1.42E-03	3.22E-04
		Teenage	1.53E-04	3.47E-05
		Adult	7.69E-05	1.75E-05
	Non-AC	Children	2.30E-03	6.10E-04
		Teenage	2.46E-04	6.55E-05
		Adult	1.24E-04	3.30E-05
Post Monsoon	**AC**	Children	3.42E-03	8.77E-04
		Teenage	3.67E-04	9.39E-05
		Adult	1.85E-04	4.74E-05
	Non-AC	Children	5.16E-03	4.95E-04
		Teenage	5.53E-04	5.31E-05
		Adult	2.79E-04	2.67E-05

3.4.1.2 | ELCR ($PM_{2.5}$: Monsoon and Post-Monsoon). **Exhibit 10** illustrates the descriptive statistics of ELCR values for $PM_{2.5}$ during the monsoon and post-monsoon seasons in both AC and Non-AC environments across three age groups.

The carcinogenic risk associated with $PM_{2.5}$ exposure varied notably between age groups, environmental conditions, and seasons (Exhibit 10). During the monsoon, children in AC environments experienced a mean ELCR of 7.16E-04, while teenagers and adults recorded lower values of 7.68E-05 and 3.87E-

EXHIBIT 10 | Descriptive statistics of excess lifetime cancer risk (ELCR) for $PM_{2.5}$ exposure by age group and indoor environment.

Seasons	Environment	Age Group	Mean ELCR	SD
Monsoon	**AC**	Children	7.16E-04	2.25E-04
		Teenage	7.68E-05	2.42E-05
		Adult	3.87E-05	1.22E-05
	Non-AC	Children	1.39E-03	3.56E-04
		Teenage	1.49E-04	3.81E-05
		Adult	7.53E-05	1.93E-05
Post Monsoon	**AC**	Children	1.70E-03	4.65E-04
		Teenage	1.83E-04	4.98E-05
		Adult	9.21E-05	2.52E-05
	Non-AC	Children	2.70E-03	2.69E-04
		Teenage	2.90E-04	2.89E-05
		Adult	1.46E-04	1.44E-05

EXHIBIT 11 | Descriptive statistics of excess lifetime cancer risk (ELCR) for HCHO exposure by age group and indoor environment.

Seasons	Environment	Age Group	Mean ELCR	SD
Monsoon	**AC**	Children	8.75E-06	1.58E-06
		Teenage	9.38E-07	1.71E-07
		Adult	4.73E-07	8.57E-08
	Non-AC	Children	4.27E-06	1.34E-06
		Teenage	4.57E-07	1.44E-07
		Adult	2.31E-07	7.24E-08
Post Monsoon	**AC**	Children	7.92E-06	1.06E-06
		Teenage	8.50E-07	1.13E-07
		Adult	4.28E-07	5.71E-08
	Non-AC	Children	5.29E-06	7.98E-07
		Teenage	5.67E-07	8.57E-08
		Adult	2.86E-07	4.32E-08

05, respectively. In non-AC environments, risks were elevated across all age groups, with children showing the highest mean ELCR of 1.39E-03. Teenagers and adults followed similar trends, registering mean ELCRs of 1.49E-04 and 7.53E-05, respectively. Post-monsoon ELCRs were considerably higher, particularly in non-AC settings. Children's mean risk in non-AC environments reached 2.70E-03, nearly 1.6 times higher than in AC conditions (1.70E-03). Teenagers and adults also exhibited increased risks in non-AC environments, with mean ELCRs of 2.90E-03 and 1.46E-03, compared to 1.83E-03 and 9.21E-05 in AC environments.

3.4.1.3 | ELCR (HCHO: Monsoon and Post-Monsoon). The Estimated Lifetime Cancer Risk (ELCR) for formaldehyde (HCHO) exposure is summarized in **Exhibit 11** for three age groups in both AC and non-AC environments across monsoon and post-monsoon seasons.

During the monsoon, children in AC environments showed the highest mean ELCR of 8.75E-06, followed by teenagers (9.38E-07) and adults (4.73E-07). In non-AC settings, risks were slightly lower for children (4.27E-06) and consistently lower across teenagers (4.57E-07) and adults (2.31E-07). In the post-monsoon season, the mean ELCR for children remained relatively stable, with 7.92E-06 in AC environments and 5.29E-06 in non-AC environments. Teenagers and adults followed the same trend, with AC values of 8.50E-07 and 4.28E-07, and non-AC values of 5.67E-07 and 2.86E-07, respectively.

3.4.2 | Non-Carcinogenic Health Risk

3.4.2.1 | HQ ($PM_{2.5}$: Monsoon and Post-Monsoon). The non-carcinogenic health risk associated with $PM_{2.5}$ exposure, expressed as the Hazard Quotient (HQ), showed notable differences across seasons and indoor environments (**Exhibit 12**).

During the monsoon, AC environments recorded a mean HQ of 2.07, with a standard deviation of 0.65, indicating moderate

EXHIBIT 12 | Descriptive statistics of hazard quotient (HQ) for $PM_{2.5}$ exposure by indoor environment.

Seasons	Environment	Mean HQ	SD
Monsoon	**AC**	2.07	0.65
	Non-AC	4.02	1.03
Post Monsoon	**AC**	4.91	1.34
	Non-AC	7.79	0.78

EXHIBIT 13 | Descriptive statistics of Hazard Quotient (HQ) for PM_{10} exposure by indoor environment.

Seasons	Environment	Mean HQ	SD
Monsoon	**AC**	0.76	0.17
	Non-AC	1.53	0.38
Post Monsoon	**AC**	1.67	0.47
	Non-AC	2.78	0.28

variation across sampling locations. Non-AC environments presented a higher mean HQ of 4.02 (SD = 1.03), reflecting elevated potential risk due to reduced air filtration and ventilation. In the post-monsoon season, HQ values increased markedly. AC environments exhibited a mean HQ of 4.91 (SD = 1.34), while non-AC settings showed the highest potential risk, with a mean HQ of 7.79 (SD = 0.78). Maximum HQ values reached 7.07 in AC and 9.30 in non-AC environments, highlighting substantial exposure differences between indoor conditions.

3.4.2.2 | HQ (PM_{10}: Monsoon and Post-Monsoon). The non-carcinogenic risk associated with PM_{10} exposure, measured as the Hazard Quotient (HQ), was generally lower than that for PM_{10} but demonstrated clear seasonal and environmental differences (**Exhibit 13**).

During the monsoon, AC environments exhibited a mean HQ of 0.76 with a standard deviation of 0.17, indicating relatively low health risk. Non-AC settings, however, showed nearly double the mean HQ at 1.53 (SD = 0.38), highlighting the influence of indoor ventilation and air-conditioning on pollutant accumulation. Post-monsoon HQ values increased across all environments. In AC conditions, the mean HQ rose to 1.67 (SD = 0.47), whereas non-AC environments presented the highest potential risk, with a mean HQ of 2.78 (SD = 0.28). Maximum values reached 2.49 in AC and 3.21 in non-AC environments, emphasizing elevated exposure levels during the post-monsoon season.

4 | Discussion

The findings of this study illuminate a troubling portrait of IAQ in Mymensingh City, Bangladesh, where both AC and Non-AC environments harbor distinct yet severe pollution challenges. By contextualizing these results within the broader scientific discourse and regional studies, this discussion synthesizes how the observed trends align with or challenge existing literature while underscoring the urgency of localized interventions.

Non-AC environments, reliant on natural ventilation, exhibited significantly higher PM_1, $PM_{2.5}$, and PM_{10} concentrations, with post-monsoon $PM_{2.5}$ levels in Non-AC rooms exceeding WHO guidelines by 8 times (Exhibit 4). This aligns with studies in Dhaka (Yasmin et al. 2024) and Lahore (Nimra et al. 2021), where reliance on natural ventilation in urban areas led to indoor PM levels reflecting outdoor pollution. For instance, Nahian et al. (2024) reported average $PM_{2.5}$ concentrations of 121 $\mu g/m^3$ in Dhaka households, nearly double to this study's Non-AC monsoon averages (67.21 $\mu g/m^3$). The seasonal spike in particulate matter during post-monsoon months correlates with reduced rainfall and increased resuspension of road dust, construction activities, and biomass burning, a pattern documented in Khulna by Saju et al. (2023).

AC systems reduced PM infiltration by 25%–49% during the monsoon season and approximately 33%–43% during the post-monsoon season, which closely aligns with Montgomery et al. (2015), who found mechanical ventilation lowered $PM_{2.5}$ by approximately 42% in Canadian offices. However, even AC rooms in Mymensingh exceeded WHO $PM_{2.5}$ limits by approximately 2.6 times during post-monsoon, underscoring the limitations of filtration in regions with extreme ambient PM pollution. This contrasts with the findings of Zaki and Bari (2022) in Malaysian schools, where AC systems maintained $PM_{2.5}$ below 10 $\mu g/m^3$, highlighting the role of outdoor air quality in dictating IAQ.

AC environments paradoxically harbored higher TVOC and HCHO levels (Exhibit 5). This aligns with the seminal study in Singapore by Wong and Huang (2004), where AC bedrooms had 46% higher formaldehyde than naturally ventilated spaces due to sealed environments trapping emissions from furniture and cleaning agents. Similarly, Suwanaruang (2023) identified AC-dependent shopping malls in Thailand as TVOC hotspots (0.99 mg/m^3), driven by poor ventilation and chemical off-gassing. In Mymensingh, the widespread use of low-cost composite wood products in urban buildings, a consequence of rapid, unregulated construction, use of lower-quality wall paints, and certain cleaning products likely exacerbates TVOC and HCHO levels. The post-monsoon surge in TVOCs (749 $\mu g/m^3$ in AC rooms) aligns with Kalia et al. (2024), who attributed midday TVOC peaks in Indian apartments to temperature-driven emissions from paints and adhesives.

Neither AC nor Non-AC environments met the WHO guidelines for $PM_{2.5}$, PM_{10}, or HCHO. While PM_{10} levels rarely exceeded the BNAAQS threshold of 150 $\mu g/m^3$, there are no national standards in Bangladesh for PM_1 or TVOCs. This regulatory gap, also highlighted by Pavel et al. (2020) in Dhaka, leaves these pollutants unregulated. To put things into perspective, PM_1 levels in Non-AC rooms in Mymensingh averaged 89.32 $\mu g/m^3$, strikingly similar to outdoor PM_1 levels in Khulna City (143 ± 45.05 $\mu g/m^3$) (Saju et al., 2023). Despite this, Bangladesh lacks policies specifically addressing ultrafine particles. Without proper regulations, these invisible pollutants continue to pose serious health risks, especially in densely populated urban areas where poor infrastructure exacerbates air quality issues.

The correlation analysis (Exhibit 7) showed that temperature had a positive effect on PM levels but a negative effect on HCHO. These results align with Belias and Licina (2022), who found that when temperatures rise by 5°C, $PM_{2.5}$ infiltration increases by 10%–15% in naturally ventilated spaces. In the Non-AC rooms of Mymensingh city, where afternoon temperatures reached 34°C, this likely caused more PM to be stirred up from the floors and brought in from outside. This is consistent with Cho et al. (2021), who found that high temperatures lead to about 15% more PM particles clumping together. On the other hand, AC rooms with cooler temperatures (24–26°C) may have reduced PM movement but increased HCHO emissions. This happens because materials like plywood release more formaldehyde in cooler, less ventilated spaces (Wiglusz et al. 2002).

Humidity had only a weak connection with PM levels ($r = -0.09$ to 0.04) but showed a moderate negative relationship with TVOCs ($r = -0.32$) and HCHO ($r = -0.46$). This supports the findings of Zhou et al. (2019), who reported that humidity above 70% can increase VOC emissions from damp materials by 20%–50%. During the monsoon season in Mymensingh City, humidity levels reached 85%–99%, which may have helped reduce TVOC levels in Non-AC rooms by making pollutants settle faster. However, AC systems, which lower indoor humidity to 50%–60%, may have accidentally created the perfect conditions for VOC buildup.

The PMF source apportionment analysis provided further insight into pollutant origins and interactions. AC rooms typically exhibited distinct source separation, with particulate-dominated, TVOC-dominated, and HCHO-dominated factors corresponding to outdoor infiltration, indoor activities, and emissions from building materials, respectively (Exhibit 8a, 8c). Non-AC environments, in contrast, showed more mixed source profiles, reflecting overlapping contributions from outdoor infiltration, indoor chemical sources, and resuspension processes (Exhibit 8b, 8d). Post-monsoon conditions intensified the complexity of indoor sources, particularly in Non-AC rooms, where high PM_1 and HCHO loadings indicated a combined effect of ultrafine particles and formaldehyde emissions. These interactions highlight that ventilation type not only influences pollutant concentrations but also modulates the relative contribution of different sources under varying seasonal and microclimatic conditions.

Children faced the highest Excess Lifetime Cancer Risk (ELCR) from PM_1 (5.16E-03), $PM_{2.5}$ (2.7E-03), and HCHO (8.75E-06), exceeding the safety limits set by the USEPA (Exhibits 3, 9, and 10). Although variations between AC and non-AC environments were observed, the risks in both settings remained significantly higher than recommended thresholds set by the health authorities. These risks were even higher than those reported in Tehran (Yunesian et al. 2019) and in Ardebil (Rostami et al. 2019), where the ELCR for $PM_{2.5}$ reached a maximum of 3.06E-04, but closely aligns with Pavel et al. (2020). High-risk zones (e.g., SP5-SP28) were mostly clustered in the central business district of Mymensingh city (supplementary data), where traffic pollution and commercial activities contribute heavily to poor air quality. A similar pattern was observed in Khulna by Saju et al. (2023), highlighting how urban centers with high human activity tend to have greater pollution-related health risks.

The hazard quotient (HQ) analysis reveals that $PM_{2.5}$ exposure in Mymensingh's indoor environments poses severe non-carcinogenic health risks, with values consistently exceeding safe thresholds across all studied settings. In Non-AC rooms during the post-monsoon season, HQ values reached alarming levels of 9.30 (Exhibit 11), indicating that daily $PM_{2.5}$ exposure was 9.3 times higher than the reference dose (RfD) established by health authorities. Even in AC environments, where mechanical filtration provided partial protection, HQ values remained elevated at 7.07, indicating substantial risk. For PM_{10}, risks were comparatively lower but still exceeded unity, the threshold for potential adverse effects. Non-AC environments showed the greatest risk, with mean HQ values of 1.53 in the monsoon and 2.78 in the post-monsoon, while AC settings recorded lower but still concerning means of 0.76 and 1.67, respectively (Exhibit 12). These findings align with recent studies in comparable Asian urban environments. Saju et al. (2023) reported similar HQ elevations (20.13 for $PM_{2.5}$ and 8.3 for PM_{10}) in Khulna city, while Pavel et al. (2020) found lower but still concerning HQ values (2.11) in Dhaka city. Yunesian et al. (2019) reported similar HQ elevations (6.3 for $PM_{2.5}$) in Tehran residences.

The particularly high HQ values in Mymensingh households reflect the city's unique combination of high ambient pollution and prevalent use of natural ventilation, creating a perfect storm for indoor particulate accumulation.

5 | Conclusion

Indoor air pollution has become a major public health concern in Bangladesh due to rapid urbanization, industrialization, and increasing human exposure to harmful pollutants. The present findings demonstrate that indoor air pollution is strongly influenced by ventilation type, seasonal variation, and indoor microclimatic conditions. Non-AC environments consistently experienced higher concentrations of particulate matter, particularly during the post-monsoon season, whereas AC environments showed greater accumulation of formaldehyde and TVOCs, reflecting the effect of limited air exchange in mechanically ventilated spaces. Most measured pollutants exceeded the recommended WHO guideline values, indicating that IAQ remains a significant environmental and public health concern. The correlation analysis revealed strong positive relationships among PM_1, $PM_{2.5}$, and PM_{10}, suggesting common emission sources and similar transport mechanisms. Temperature showed positive associations with particulate matter, while formaldehyde and TVOCs were more closely associated with cooler and less ventilated indoor conditions. These findings demonstrate that seasonal meteorological conditions and indoor environmental characteristics play an important role in shaping pollutant concentrations.

Source apportionment further showed that IAQ is controlled by multiple emission sources rather than a single dominant factor. Outdoor particle infiltration, indoor resuspension, building materials, furniture, and household activities all contributed to the observed pollution patterns, although their relative importance varied between AC and Non-AC environments and across seasons. This highlights the complex interaction between indoor activities, building characteristics, and outdoor pollution.

The health risk assessment indicates that particulate matter poses the greatest public health concern, particularly for children in Non-AC environments, where both carcinogenic and non-carcinogenic risks were highest. Although AC environments reduced exposure to particulate matter, elevated formaldehyde and TVOC concentrations indicate that mechanical cooling alone cannot ensure healthy indoor air. Adequate ventilation, regular maintenance of air-conditioning systems, and effective source control are equally important for reducing exposure to harmful pollutants. The differential risk profiles between AC and Non-AC environments present a complex public health challenge. While AC spaces showed lower PM-related risks, their elevated VOC and HCHO concentrations may contribute to different health outcomes, including neurological effects and sensory irritation.

While this study provides important insights into IAQ in Mymensingh City, several limitations exist. The cross-sectional design and short monitoring period capture only seasonal trends, and the lack of particulate matter speciation limits identification of specific sources. Behavioral factors and occupancy patterns were not fully assessed, and the small sample size restricts generalizability. Future studies should include longer-term, multi-season monitoring, chemical analysis of pollutants, and broader surveys across other urban areas to improve understanding and applicability (Hossain et al., 2025). Supporting Information

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Conflicts of Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper and have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

AI Disclosure Statement

To enhance linguistic clarity and readability, the author used AI-assisted tools including **QuillBot** and **Grammarly** for grammar correction and language refinement, and **Perplexity** and **Consensus** for literature exploration and reference identification support. All manuscript text was written in the author's own words. These tools were not used for study design, data analysis, scientific interpretation, or the formulation of results and conclusions. All analyses, interpretations, and scholarly judgments presented in this manuscript were conducted independently by the authors, who collectively takes full responsibility for the scientific content, accuracy, and integrity of the work.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting information: tqem70435-sup-0001-FigureS1-S10.docx